

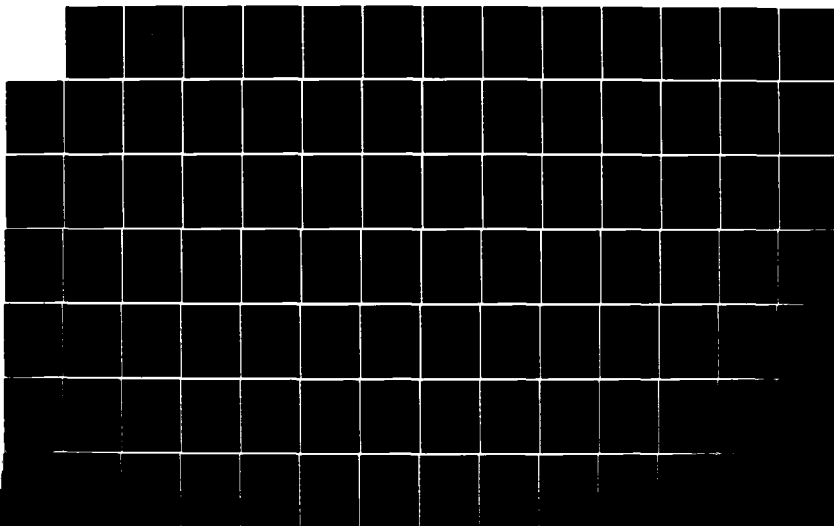
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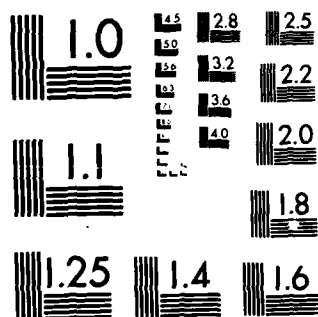
DEVELOPMENT OF REAL-TIME ERROR ELLIPSES AS AN INDICATOR 1/2
OF KALMAN FILTER PERFORMANCE (U) NAVAL POSTGRADUATE
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DEVELOPMENT OF REAL-TIME ERROR ELLIPSES
AS AN INDICATOR OF KALMAN
FILTER PERFORMANCE

by

Joseph Jaros

March 1984

Thesis Advisor:

A. Gerba, Jr.

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Development of Real-Time Error Ellipses
as an Indicator of Kalman Filter Performance

by

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B.S., University of Texas, 1967

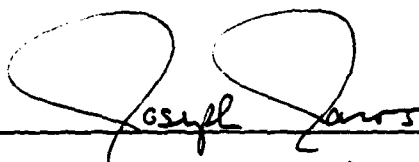
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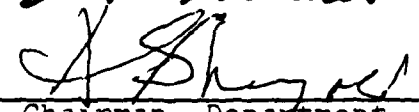
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ABSTRACT

An error ellipse plotting routine was developed to provide real-time indication of Kalman filter performance. The study included an evaluation of the Hewlett-Packard HP-86 computer system's capability for providing real-time tracking information and an evaluation of the computer's possible use on the three-dimensional underwater tracking range at the Naval Underwater Weapons Engineering Station, Keyport, Washington. A series of tracking runs were used to demonstrate both linear and extended Kalman filtering. Information obtained from the error ellipses was used to modify filter parameters for improved filter performance. It was found that the error ellipse was useful as a tool for indicating filter performance and for making decisions regarding filter parameter modification. The HP-86 provided accurate, reliable results and it could be used for on-line graphics. However, the computing speed for the HP-86 computer as used in this study was too slow for on-line processing of the three-dimensional tracking problem.

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I. INTRODUCTION

The Kalman filter's importance as an estimator and predictor is well documented. Providing real-time information concerning filter performance so that on-line adjustments to filter parameters can be made continues to be an area of high interest. This study investigates the usefulness of the error ellipse as a tool for providing a real-time indication of filter performance.

Part of the investigation involves an evaluation of the Hewlett-Packard HP-86 computer system's capacity to operate in a real time tracking environment, and its capabilities for providing information concerning filter performance. The rationale behind this investigation is based on the requirement for the Naval Underwater Weapons Engineering Station, Keyport, Washington, to accurately acoustically track torpedoes on a three-dimensional underwater tracking range. A knowledge of the range operation is not within the scope of this study. It is sufficient to know that presently the range receives four time measurements every 1.31 seconds, and these measurements are nonlinear functions of the torpedo position.

To gain a better understanding of the error ellipse, a 4-state tracking scenario was chosen for this study.

Initially, the linear tracking problem is discussed, followed by an investigation of the nonlinear problem. Of primary interest are on-line methods to improve filter performance using information provided by the error ellipse for filter parameter modification.

II. KALMAN FILTER THEORY

A. LINEAR MATHEMATICAL MODEL

1. The Plant

For this model the state and measurement equations for the plant are linear. Hence the discrete form is used. The assumed plant model is described by a linear, vector difference equation:

$$\underline{x}(k+1) = \underline{\phi}\underline{x}(k) + \underline{\Delta}u(k) + \underline{\Gamma}w(k) \quad (\text{State Equation}) \quad (2-1)$$

and a linear, vector measurement equation:

$$\underline{z}(k) = \underline{c}\underline{x}(k) + \underline{v}(k) \quad (2-2)$$

where:

$\underline{x}(k)$ is an n-dimensional column vector, denoting the state of the plant at "time" k.

$\underline{u}(k)$ is the deterministic control input, an m-vector, at time k.

$\underline{w}(k)$ is a p-dimensional vector representing any random forcing inputs at time k.

$\underline{z}(k)$ is a q-dimensional vector representing measurements made at time k.

$\underline{v}(k)$ is a q-dimensional vector representing random measurement made at time k.

$\underline{\phi}$, $\underline{\Delta}$, $\underline{\Gamma}$, and \underline{c} are assumed constant coefficient matrices of dimension nxn, nxm, nxp, and qxn respectively.

2. Noise Processes

In order to place probabilistic structure on the noise processes $\underline{v}(k)$ and $\underline{w}(k)$ the following assumptions are made:

- (a) $\underline{v}(k)$ and $\underline{w}(k)$ are individually white processes, that is, for any k and l , with $k \neq l$, $\underline{v}(k)$ and $\underline{v}(l)$ are independent random variables, and $\underline{w}(k)$ and $\underline{w}(l)$ are independent random variables.
- (b) $\underline{v}(k)$ and $\underline{w}(k)$ are individually zero mean, Gaussian processes with known covariances.
- (c) $\underline{v}(k)$ and $\underline{w}(k)$ are independent processes.

Thus for the measurement noise:

$$\text{MEAN: } E[\underline{v}(k)] = \underline{0} \quad (k=0,1,2,3,\dots) \quad (2-3)$$

$$\begin{aligned} \text{COVARIANCE: } E[\underline{v}(k)\underline{v}^T(l)] &= E[\underline{v}(k)]E[\underline{v}^T(l)] \\ &= 0 \quad k \neq l \\ &\stackrel{\Delta}{=} \underline{R}_k \quad k = l \end{aligned}$$

$$\text{or } E[\underline{v}(k)\underline{v}^T(l)] = \underline{R}_k \delta_{kl} \quad (k,l=0,1,2,\dots) \quad (2-4)$$

where δ_{kl} is the Kronecker delta function defined as:

$$\delta_{kl} \quad \begin{cases} = 0, & k \neq l \\ = 1, & k = l \end{cases}$$

Likewise for the random forcing input:

$$E[\underline{w}(k)] = \underline{0} \quad (k=0,1,2,3,\dots) \quad (2-5)$$

$$E[\underline{w}(k)\underline{w}^T(l)] \triangleq \underline{Q}_k \delta_{kl} \quad k,l=0,1,2,3,\dots \quad (2-6)$$

\underline{Q}_k and \underline{R}_k are nonnegative definite symmetric for all k . Also since $\underline{v}(k)$ and $\underline{w}(k)$ are zero mean and independent then:

$$E[\underline{v}(k)\underline{w}^T(l)] = \underline{0} \quad (2-7)$$

For the purposes of this study, unless otherwise specified \underline{Q}_k and \underline{R}_k are considered to be known and constant, although both may be time varying.

3. Initial State Description

For the initial state of the difference equation (2-1) it is unlikely that \underline{x}_0 will be available. Hence, it is assumed that \underline{x}_0 is a Gaussian random variable of known mean $\bar{\underline{x}}_0$ and known covariance \underline{P}_0 , i.e.,

$$E[\underline{x}(0)] = \bar{\underline{x}}_0$$

$$E\{[(\underline{x}_0 - \bar{\underline{x}}_0)][(\underline{x}_0 - \bar{\underline{x}}_0)]^T\} = \underline{P}_0$$

This choice for the initial state has the advantage of causing the subsequent estimation scheme to be unbiased for all τ . [Ref. 1] Further it is assumed that the initial state and the measurement noise are uncorrelated:

$$E[\underline{x}(0)\underline{v}^T(k)] = E[\underline{v}(k)\underline{x}^T(0)] = \underline{0} \quad (k=0,1,2,3,\dots)$$

Also the initial state and the random forcing input are uncorrelated:

$$E[\underline{x}(0)\underline{w}^T(k)] = E[\underline{w}(k)\underline{x}^T(0)] = \underline{0} \quad (k=0,1,2,3,\dots)$$

B. DISCRETE-TIME ESTIMATION

1. The Estimator Equations

The estimation problem involves generating an optimal estimate for $\underline{x}(j)$ for the system described by the difference equation (2-1) from the noisy measurements $\underline{z}(0), \underline{z}(1), \dots, \underline{z}(j)$. This estimate will be denoted by $\hat{\underline{x}}(j/j)$, which means the estimate of \underline{x} at time j given measurements at times up to and including time j . The estimate must be optimal in the sense that the expected value of the sum of the squares of the error in the estimate is a minimum, i.e.:

$$E\{[\hat{\underline{x}}(k/k) - \underline{x}(k)]^T [\hat{\underline{x}}(k/k) - \underline{x}(k)]\} = \text{minimum}$$

The estimator is characterized by the linear relationship:

$$\hat{\underline{x}}(k/k) = \hat{\underline{x}}(k/k-1) + \underline{G}(k)[\underline{z}(k) - \underline{c}\hat{\underline{x}}(k/k-1)] \quad (k=0,1,2,\dots) \quad (2-8)$$

where

- $\hat{\underline{x}}(k/k)$ is the optimal (minimum variance) estimate of $\underline{x}(k)$ given observations at times up to and including k .
- $\hat{\underline{x}}(k/k-1)$ is the optimal one-step prediction of $\underline{x}(k)$ given observations at times up to and including $k-1$.
- $\underline{G}(k)$ is the optimal estimation gain matrix which will minimize the variance of estimation error.

For the initial estimate $\hat{\underline{x}}(0/0)$, the estimator equation (2-8) is initialized with $\hat{\underline{x}}(0/-1)$, which is not a random variable. If $\hat{\underline{x}}(0/-1)$ is selected such that:

$$\hat{\underline{x}}(0/-1) = E[\underline{x}(0)] = \bar{\underline{x}}_0$$

it can be shown that this choice of $\hat{\underline{x}}(0/-1)$ makes the estimator unbiased for all k . [Ref. 1] The estimator's best available information concerning $\underline{x}(k-1)$ is the estimate $\hat{\underline{x}}(k-1/k-1)$, therefore it is reasonable to assume that

$$\hat{\underline{x}}(k/k-1) = \underline{\phi}\hat{\underline{x}}(k-1/k-1) + \underline{\Delta}u(k-1) \quad (2-9)$$

is the best prediction.

In summary, equations (2-8) and (2-9) are the estimator equations, with $\hat{\underline{x}}(0/-1) = \bar{\underline{x}}_0$ as the initial condition.

2. Gain and Covariance Equations

Without going into detailed derivations, the optimal estimator gains, $\underline{G}(k)$, used in the estimator equation (2-8), are those which satisfy:

$$\underline{G}(k) = \underline{P}(k/k-1)\underline{C}^T[\underline{C}\underline{P}(k/k-1)\underline{C}^T + \underline{R}]^{-1} \quad (2-10)$$

$$\underline{P}(k/k) = [\underline{I} - \underline{G}(k)\underline{C}]\underline{P}(k/k-1) \quad (2-11)$$

$$\underline{P}(k+1/k) = \underline{\phi}\underline{P}(k/k)\underline{\phi}^T + \underline{Q} \quad (2-12)$$

with the initial conditions:

$$\underline{P}(0/-1) \triangleq \underline{P}_0 = E\{[\underline{x}(0) - \bar{\underline{x}}_0][\underline{x}(0) - \bar{\underline{x}}_0]^T\}$$

where

$$\underline{P}(k/k) = E\{[\hat{\underline{x}}(k/k) - \underline{x}(k)][\hat{\underline{x}}(k/k) - \underline{x}(k)]^T\}$$

is the covariance of estimation error matrix.

$$\underline{P}(k/k-1) = E\{[\hat{\underline{x}}(k/k-1) - \underline{x}(k)][\hat{\underline{x}}(k/k-1) - \underline{x}(k)]^T\}$$

is the covariance of one-step prediction error matrix.

$$\underline{Q} = E[\underline{\Gamma}(k) \cdot \underline{w}(k) \cdot \underline{w}^T(k) \cdot \underline{\Gamma}^T(k)]$$

is the state excitation matrix.

$\underline{P}(k/k)$ and $\underline{P}(k/k-1)$ are symmetric, positive definite matrices.

Several observations can be made concerning the linear Kalman gain (2-10), covariance (2-11, 2-12) and estimator (2-8) equations.

(a) The estimator gains, $\underline{G}(k)$, do not depend on the measurement data and hence can be precomputed, stored, and used as the processing measurements become available.

(b) Although not obvious from the equation, the time-varying gain, $\underline{G}(k)$, depends in time as:

$$\underline{G}(k) = \frac{1}{(k+1)} \quad [\text{Ref. 2}] \quad (2-13)$$

Thus the effect is to weight the correction term, $[\underline{z}(k) - \underline{c}\underline{x}(k/k-1)]$, in the estimator equation (2-8) less heavily as time progresses. The advantage of a greater initial weight allows for possibly large differences between $\underline{z}(k)$ and $\underline{x}(k/k-1)$ during the initial observations, and a large gain will result in a significant change in the

next estimate. This advantage is also borne out in that there is less confidence in the quality of the estimates during the early observations compared with the quality after numerous observations. Hence the later an observation, the less drastic an estimate will be altered or affected by an isolated observation discrepancy.

(c) In general, the variance of estimation error decreases in a manner analogous to the gain schedule (2-13), i.e., it decreases as k grows larger, reflecting greater confidence in the estimate as the number of observations increases. Selection of the proper initial condition, \underline{P}_0 , is important when studying the effect of measurement errors on the behavior of the estimate. So \underline{P}_0 should be assigned pessimistic values which would correspond to a lack of information about the initial state. In cases when the initial state is completely unknown, then $\underline{P}_0 \rightarrow \infty \mathbf{I}$. [Ref. 3]

(d) The \underline{Q} matrix serves to compensate for model errors and prevents the covariance matrix from becoming too small or optimistic. A small covariance matrix would result in a small filter gain, and subsequent observations are essentially ignored, which could result in filter divergence. The \underline{Q} matrix prevents $\underline{G}(k)$ from approaching zero by adding uncertainty to the system which is reflected in a degradation of certainty (increase in $\underline{P}(k+1/k)$).

C. NONLINEAR ESTIMATION - EXTENDED KALMAN FILTER

In many practical applications, the state equations and/or measurement equations are nonlinear. Before the Kalman filter equations can be used, the problem must be linearized and the Kalman filter equations are applied with some modification.

1. Nonlinear Model

Consider a nonlinear discrete system of state and observation equations given by:

$$\underline{x}(k+1) = \underline{f}(\underline{x}(k), \underline{u}(k), k) + \underline{w}(k) \quad (2-14)$$

and

$$\underline{z}(k) = \underline{h}(\underline{x}(k), k) + \underline{v}(k) \quad (2-15)$$

In these equations \underline{f} and \underline{h} are nonlinear functions of the state variable \underline{x} , $\underline{w}(k)$ is the plant excitation noise, and $\underline{v}(k)$ is the measurement noise. The plant noise and measurement noise are assumed to be uncorrelated, zero-mean, and white. The same equations (2-3 thru 2-7) apply as for the linear model.

2. Extended Kalman Filter Equations

In order to apply the linear filter equations, equations (2-14) and (2-15) are expanded about the best estimate of the state at that time and only the first-order terms are kept.

That is, defining $A(k)$ as:

$$\underline{A}(k) = \left. \frac{\partial \underline{f}}{\partial \underline{x}} \right|_{(\hat{\underline{x}}(k/k), \underline{u}(k), k)}$$

and

$$\underline{H}(k) = \left. \frac{\partial \underline{h}}{\partial \underline{x}} \right|_{(\hat{\underline{x}}(k/k-1))}$$

As can be seen from the above equations, the filter estimates, $\hat{\underline{x}}(k/k)$ and $\hat{\underline{x}}(k/k-1)$ are used as the "best" estimates about which the linearization is performed. The matrices $\underline{A}(k)$ and $\underline{H}(k)$ must be used to generate $\underline{G}(k)$ so it is available to process $\underline{z}(k)$ when it is obtained. The modified extended Kalman filter equations are then:

Gain Equation:

$$\underline{G}(k) = \underline{P}(k/k-1) \underline{H}^T(k) [\underline{H}(k) \cdot \underline{P}(k/k-1) \cdot \underline{H}^T(k) + \underline{R}]^{-1} \quad (2-16)$$

Filter Update Equation:

$$\hat{\underline{x}}(k/k) = \hat{\underline{x}}(k/k-1) + \underline{G}(k) [\underline{z}(k) - \underline{h}(\hat{\underline{x}}(k/k-1))] \quad (2-17)$$

Prediction Equation:

$$\hat{\underline{x}}(k+1/k) = \underline{f}(\hat{\underline{x}}(k/k), \underline{u}(k), k) \quad (2-18)$$

Covariance of Estimation Error Equations:

$$\underline{P}(k/k-1) = \underline{A}(k-1)\underline{P}(k-1/k-1)\underline{A}^T(k-1) + \underline{Q}(k-1) \quad (2-19)$$

$$\underline{P}(k/k) = [\underline{I} - \underline{G}(k)\underline{H}(k)]\underline{P}(k/k-1) \quad (2-20)$$

For the initial estimate $\hat{\underline{x}}(0/0)$, equation (2-17) is initialized with $\hat{\underline{x}}(0/-1)$ with

$$\hat{\underline{x}}(0/-1) = E[\underline{x}(0)] = \bar{\underline{x}}_0$$

$\hat{\underline{x}}(0/-1)$ is also used to initially evaluate $\underline{H}(k)$.

As in the linear case:

$$\underline{P}(0/-1) = \underline{P}_0 = E[(\underline{x}_0 - \bar{\underline{x}}_0)(\underline{x}_0 - \bar{\underline{x}}_0)^T]$$

III. ERROR ELLIPSOIDS

A. THEORY

Since the estimate $\hat{\underline{x}}(k/k)$ is unbiased in the Kalman filter equations, the $\underline{P}(k/k)$ matrix represents the covariance of the error in the estimate. If the estimate were biased, $\underline{P}(k/k)$ would represent the second-moment matrix rather than the covariance matrix. Hence, $\underline{P}(k/k)$ provides significant information about the accuracy of the estimate. If the physical model is accurately described by the state and measurement equations (2-1, 2-2), then $\underline{P}(k/k)$ can be used to describe the manner in which the estimate converges (or diverges) to the true state. Examination of the $\underline{P}(k/k)$ matrix directly, element by element, is not a realistic approach, since the matrix contains n^2 elements, where n is the number of state variables. To simplify the situation the concept of the error ellipsoid is used. [Ref. 4]

As discussed earlier, the assumptions are made that the initial state of the plant \underline{x}_0 is Gaussian, as are the random processes $\underline{v}(k)$ and $\underline{w}(k)$. Using these assumptions it follows that $\underline{x}(k)$ and $\hat{\underline{x}}(k/k)$ are also Gaussian since they are linear combinations of Gaussian variables and deterministic quantities. Using the same rationale, the estimation error, defined as:

$$\underline{e}(k/k) \triangleq \hat{\underline{x}}(k/k) - \underline{x}(k)$$

is also Gaussian. Using the fact that the mean of the estimation error is 0, the probability density function for $\underline{e}(k/k)$ is:

$$p_e[\underline{e}(k/k)] = [(2\pi)^{n/2} |\underline{P}(k/k)|^{1/2}]^{-1} \exp[-1/2 \underline{e}^T(k/k) \underline{P}^{-1}(k/k) \underline{e}(k/k)] \quad (3-1)$$

The density function, $p_e[\underline{e}(k/k)]$ will have a constant value whenever the exponent has a constant value. That is:

$$-1/2 \underline{e}^T(k/k) \underline{P}^{-1}(k/k) \underline{e}(k/k) = c$$

or

$$\underline{e}^T(k/k) \underline{P}^{-1}(k/k) \underline{e}(k/k) = c^2 \quad (3-2)$$

where c is an arbitrary constant.

As demonstrated by Sorenson [Ref. 1] and Kirk [Ref. 2], it can be shown that the locus of points $\underline{e}(k/k)$ which satisfy equation (3-2) are hyperellipsoids. For the two-dimensional case which is of concern, equation (3-2) describes an ellipse. This can be seen by fixing time and rewriting (3-2) as:

$$\underline{e}^T \underline{w} \underline{e} = c^2 \quad (3-3)$$

where

$$\underline{w} = \underline{p}^{-1} (k/k) \quad (\text{a } 2 \times 2 \text{ symmetric matrix})$$

Expanding the left side of (3-3) gives:

$$w_{11}e_1^2 + w_{12}w_{21}e_1e_2 + w_{22}e_2^2 = c^2$$

which because of symmetry gives:

$$w_{11}e_1^2 + 2w_{12}e_1e_2 + w_{22}e_2^2 = c \quad (3-4)$$

Since $w_{11} > 0$, $w_{22} > 0$, and $w_{11}w_{22} > w_{12}^2$, equation (3-4) describes an ellipse, in which the principal axes do not coincide with the coordinate axes. The ellipse is rewritten in terms of $\underline{y}(1)$ and $\underline{y}(2)$ as the coordinate axis, and it can be shown that $\underline{y}(1)$ and $\underline{y}(2)$ are the eigenvectors of \underline{w} with λ_1 and λ_2 defined as the corresponding eigenvalues. [Ref. 2] (See Figure 3-1). The equation for the ellipse can be rewritten in terms of a coordinate system having unit vectors in the directions of $\underline{y}(1)$ and $\underline{y}(2)$ as the basis vectors.

The ellipse equation becomes:

$$\lambda_1 \underline{y}^2(1) + \lambda_2 \underline{y}^2(2) = c^2 \quad (3-5)$$

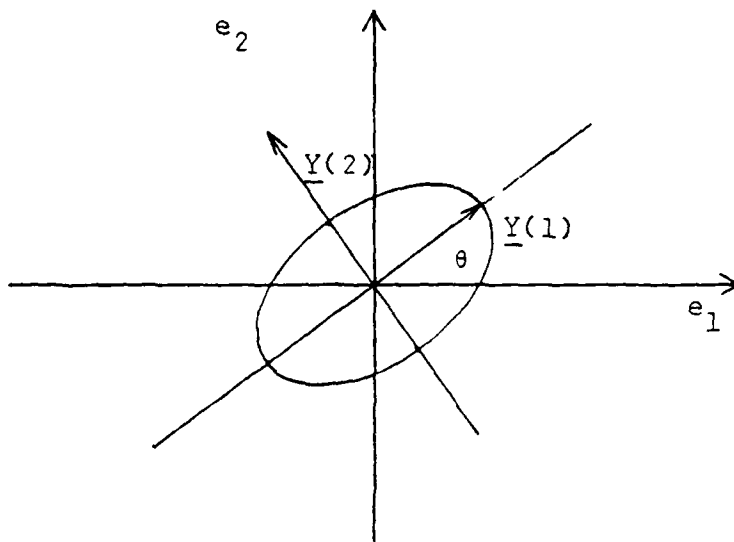


Figure 3-1 Error Ellipse

Remembering that $\underline{w} = \underline{P}^{-1}(\underline{k}/k)$, it can be shown that the corresponding eigenvectors and eigenvalues for $\underline{w}^{-1} = \underline{P}(\underline{k}/k)$ are $\underline{y}(1)$, $\underline{y}(2)$, α_1 , and α_2 , where $\alpha_1 = \frac{1}{\lambda_1}$ and $\alpha_2 = \frac{1}{\lambda_2}$. Equation (3-5) can be rewritten:

$$\frac{\underline{y}^2(1)}{\alpha_1} + \frac{\underline{y}^2(2)}{\alpha_2} = c^2 \quad (3-6)$$

For the purposes of this study, the term error ellipsoid refers to the specific case when $c = 1$. So equation (3-6) becomes:

$$\frac{y^2(1)}{a_1} + \frac{y^2(2)}{a_2} = 1$$

In terms of the Cartesian coordinates x' , y' , which use e_1 and e_2 as basis vectors:

$$x' = x \cos \theta + y \sin \theta$$

$$y' = -x \sin \theta + y \cos \theta$$

where θ is the angle of rotation of the axes and can be computed from:

$$\theta = 1/2 \tan^{-1} \left[\frac{2 \text{cov}(e_x e_y)}{\text{var}(e_x) - \text{var}(e_y)} \right] \quad [\text{Ref. 5}]$$

For a given value of c it is possible to integrate the probability density over the surface of the error ellipse to obtain the probability that a particular sample point will lie within the ellipsoid. For this study, $n = 2$, $c = 1$, and the probability the error is inside the ellipse is 0.394.

In summary, the error ellipsoid can be used to characterize the concentration of the estimate about the

true value of the state. A decrease in the magnitude of an axis of the ellipse is an indication that the error in the estimate is decreasing in that direction.

One important item that needs to be pointed out is that often the components of the state vector represent entirely different types of variables, for example the components might represent range, velocity, and depth. Since the two-dimensional ellipses are determined by using two components of the state vector, it is reasonable to examine submatrices relating state variables of the same character. Doing so will preclude most scaling difficulties when plotting the ellipses, and provide more meaningful insight in to the results.

B. ERROR ELLIPSOIDS AND FILTER DIVERGENCE

Thus far the discussion has centered around using submatrices of the $\underline{P}(k/k)$ covariance of estimation error matrix as the input for the error ellipse to indicate filter performance. As proposed by Heffes [Ref. 6] and Nishimura [Ref. 7], $\underline{P}(k/k)$ can be considered as a "design" covariance matrix \underline{P}^d , using the assumption that the only errors are in \underline{Q}_k , \underline{R}_k , and \underline{P}_0 with the following inequalities holding for all k:

$$\underline{Q}_k^d \geq \underline{Q}_k^a, \quad \underline{R}_k^d \geq \underline{R}_k^a, \quad \underline{P}_0^d \geq \underline{P}_0^a \quad (3-7)$$

with the subscript "d" indicating designed and "a" indicating actual. Equation (3-7) implies more input noise, more measurement noise, and more initial state uncertainty in the design than actually exists. This conservative filter design results in a somewhat pessimistic design error covariance $\underline{P}^d(k/k)$. The actual error covariance $\underline{P}^a(k/k)$ resulting from using a filter designed with \underline{Q}^d , \underline{R}^d , and \underline{P}_0^d is related to the design error covariance in the following manner:

$$\underline{P}^d(k/k) \geq \underline{P}^a(k/k)$$

This result is particularly useful when one simply does not know accurately the noise covariance of the input or output, but an upper bound is known. Designing assuming the noise covariance is at its upper bound will result in $\underline{P}^a(k/k)$ being upper bounded by $\underline{P}^d(k/k)$. In some sense a worst case design results. Filter divergence exists when the design error covariance $\underline{P}^d(k/k)$ remains bounded while the error performance matrix $\underline{P}^a(k/k)$ becomes very large relative to $\underline{P}^d(k/k)$ or is, in fact, unbounded.

IV. PROBLEM DEFINITION

A. PROBLEM DESIGN

The purpose of the tracking problem is to study the use of error ellipsoids as real-time indicators of filter performance. In order to keep the design model realistic albeit reasonably simplified for ease of study, a two-dimensional tracking problem using several different tracks has been selected.

1. Linear Tracking

All tracks are based on an x-y coordinate system with the target moving in the x or y direction relative to the sensor located at the origin. Thus for aircraft tracking, altitude is considered constant, as is depth for torpedo tracking.

Defining the state variables as:

- $x_1 = x$ x-coordinate of the target location.
- $x_2 = \dot{x}$ velocity of target (v_x) in x-direction.
- $x_3 = y$ y-coordinate of the target location.
- $x_4 = \dot{y}$ velocity of target (v_y) in y-direction.

resulting in a state vector:

$$\tilde{x} = \begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \end{bmatrix} \quad (4-1)$$

The following are the state equations:

$$\dot{x}_1(t) = x_2(t)$$

$$\dot{x}_2(t) = w_1(t)$$

$$\dot{x}_3(t) = x_4(t)$$

$$\dot{x}_4(t) = w_2(t)$$

(4-2)

where $w_1(t)$ and $w_2(t)$ are assumed to be uncorrelated, random processes that account for unknown target accelerations and nonlinear target motions. Writing the discrete form of the state equations gives:

$$x_1(k+1) = x_1(k) + T \cdot x_2(k) + \frac{T^2}{2} \cdot w_1(k)$$

$$x_2(k+1) = x_2(k) + T \cdot w_1(k)$$

(4-3)

$$x_3(k+1) = x_3(k) + T \cdot x_4(k) + \frac{T^2}{2} \cdot w_2(k)$$

$$x_4(k+1) = x_4(k) + T \cdot w_2(k)$$

or

$$\underline{x}(k+1) = \underline{\phi}\underline{x}(k) + \underline{\Gamma}w(k)$$

(4-4)

With T, the sampling period equal to 1 second, the matrices

$\underline{\phi}$ and $\underline{\Gamma}$ are:

$$\underline{\phi} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\underline{\Gamma} = \begin{bmatrix} .5 & 0 \\ 1 & 0 \\ 0 & .5 \\ 0 & 1 \end{bmatrix}$$

(4-5)

It is assumed that the sensor gives noisy, but uncorrelated measurements of x and y. Hence the discrete measurement equations are:

$$z_1(k) = x_1(k) + v_1(k)$$

(4-6)

$$z_2(k) = x_3(k) + v_2(k)$$

with $v_1(k)$ and $v_2(k)$ uncorrelated random noise.

Thus for the measurement equation:

$$\underline{z}(k) = \underline{c}x(k) + \underline{v}(k)$$

(4-7)

the matrix \underline{c} is:

$$\underline{c} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

For the initial run and unless otherwise noted the following values for the Gaussian random processes will be used:

$$E[\underline{v}(k)] = \underline{0} \text{ for all } k$$

$$E[\underline{v}(k)\underline{v}^T(k)] = \begin{bmatrix} 20 \times 10^3 & 0 \\ 0 & 20 \times 10^3 \end{bmatrix} \quad m^2 = \underline{R} \text{ for all } k$$

$$\underline{\sigma}_v = \begin{bmatrix} 150 \\ 150 \end{bmatrix} \quad m = \text{the standard deviation of measurement noise.}$$

$$E[\underline{w}(k)] = \underline{0} \text{ for all } k$$

$$E[\underline{w}(k)\underline{w}^T(k)] = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix} (m/sec^2)^2 = \text{cov } w \text{ for all } k$$

$$\underline{\sigma}_w = \begin{bmatrix} 10 \\ 10 \end{bmatrix} \quad m/sec^2 = \text{the standard deviations of the random forcing input.}$$

The covariance of estimation error matrix is initialized:

$$\underline{P}_0 = \underline{P}(0/-1) = \begin{bmatrix} 10^2 & 0 & 0 & 0 \\ 0 & 10^2 & 0 & 0 \\ 0 & 0 & 10^2 & 0 \\ 0 & 0 & 0 & 10^2 \end{bmatrix}$$

Since the filter is to be unbiased, the initialization:

$$\hat{\underline{x}}(0/-1) = \bar{\underline{x}}_0 = \text{Initial condition of the problem.}$$

2. Nonlinear Tracking

The state equations are the same as for the linear tracking problem. The measurement equation is considered as a noisy range measurement by the tracking sensor and is characterized as:

$$z(k) = [x_1^2(k) + x_3^2(k)]^{1/2} + v_1(k) \quad (4-8)$$

Thus $z(k)$ is a nonlinear function of the states. Using equation (2-14) and with $T = 1$ second:

$$\underline{f}(\underline{x}(k), \underline{u}(k), k) = \begin{bmatrix} x_1(k) + x_2(k) \\ x_2(k) \\ x_3(k) + x_4(k) \\ x_4(k) \end{bmatrix}$$

Taking partial derivatives of \underline{f} with respect to \underline{x} gives:

$$\underline{A}(k) = \left. \frac{\partial \underline{f}}{\partial \underline{x}} \right|_{(\hat{\underline{x}}(k/k), \underline{u}(k), k)} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} = \underline{I}$$

using equation (2-15):

$$\underline{h}(\underline{x}(k), k) = [x_1^2(k) + x_3^2(k)]^{1/2}$$

and taking the partial derivative with respect to \underline{x} gives:

$$\underline{H}(k) = \left. \frac{\partial \underline{h}}{\partial \underline{x}} \right|_{(\underline{x}(k/k-1))} = \begin{bmatrix} \frac{x_1(k)}{[x_1^2(k) + x_3^2(k)]^{1/2}}, 0, \\ \frac{x_3(k)}{[x_1^2(k) + x_3^2(k)]^{1/2}}, 0 \end{bmatrix} \bigg|_{\hat{\underline{x}}(k/k-1)}$$

Using the above results with the same values for the random noise processes as previously stated for the linear case, the extended Kalman filter equations can now be applied to the nonlinear tracking problem.

B. COMPUTER SIMULATION

1. Computer Hardware/Software

a. Hardware

All computer simulations were run on the Hewlett-Packard HP-86 personal computer. This particular model was chosen to evaluate its capabilities in determining its usefulness in actual torpedo tracking at the underwater tracking range at Naval Underwater Weapons Engineering Station, Keyport, Washington. The HP-86 system used included keyboard, 9 inch CRT monitor connected through an integrated monitor interface, and two HP Flexible Disc Drives connected through an integrated disc interface. Plotting was done on a HP-7225B Plotter and printing on a HP-2631G Printer. These peripherals were interfaced using a HP-IB Interface module. Because the system uses interface select codes, the HP-IB factory preset code was set at 7, which is the select code for the printer/disc interface. This code however did not work when interfacing with the external plotter and printer, since duplicate select codes are not allowed. So the internally set select code of the HP-IB was set to 8 for proper system operation.

b. Software

The HP-86 has 60K built-in, useable bytes of computer memory, expandable to 572K using either 32K, 64K, or 128K Memory Modules. A HP-86 plug-in ROM was required to operate the external plotter. Also a Matrix ROM was used to reduce program length and computer run time.

All programs were written in BASIC programming language using REAL (full) precision, which provides 15 digit precision. Appendix B provides an explanation of the program options and Appendix C contains the program listings used for this study.

2. Track Generation

To evaluate the real-time use of the error ellipse as an indicator of filter performance, Monte Carlo simulation runs were made. Four tracks were generated by separate programs and one second incremental values of x , y , v_x , and v_y were stored in data files. Appendix I contains an explanation of the generation of tracks three and four.

3. Noise Generation

In order to simulate the random noise processes, the computer's random number generator was used and the generated numbers scaled accordingly. For each track and each different value of noise sigma, a different generator "seed number" was used. These noise values produced were added to the applicable true track values to simulate a sensor measurement corrupted by independent Gaussian noise. For all

cases where filter parameters were varied for a particular track under a specific noise condition, one noisy track was generated, stored, and used throughout that particular simulation. This was done for ease of filter performance comparison.

4. Gating Scheme

In order to preclude catastrophic filter failure due to excessive measurement noise, a bound was established for the maximum acceptable limits of measurement noise. A three-sigma gate was designed using the covariance of the measurement noise, R , and the predicted covariance of error matrix $P(k/k-1)$. The gate is defined as:

$$\text{Gate}(k) = 3(p_{ii_{\max}}(k/k-1) + R_{ii})^{1/2}$$

This gate is the maximum error allowable for the measurement at time k . If the absolute difference between the actual measurement received and the predicted measurement is greater than the three-sigma gate, then that particular measurement data is rejected as unacceptable. When this occurs, the filter gain, $\underline{g}(k)$, is set to zero, resulting in that measurement being ignored and the prediction of the states set equal to the estimate, that is:

$$\underline{x}(k/k) = \underline{x}(k/k+1)$$

5. Collection of Statistics

In order to study error ellipses as an indicator of filter performance, statistics were calculated, on line, after each measurement during the Monte Carlo run. The statistics computed were relative error (in some cases the error was normalized), error mean, error variance, and error covariance for the positional variables. The following equations apply:

$$\text{Relative Error} = \underline{e}(k/k) = \underline{x}(k) - \hat{\underline{x}}(k/k)$$

(filter error residual)

$$\text{Error Mean} = \bar{\underline{e}}(k/k) = 1/k \sum_{j=1}^k \underline{e}(j/j)$$

$$\text{Error Variance} = \text{Var}[\underline{e}_i(k/k)] = 1/k \sum_{j=1}^k [\underline{e}_i(j/j)] - [\bar{\underline{e}}_i(k/k)]^2$$

$$i = x_1, x_2, x_3, x_4$$

Positional
Error
Covariance =
Matrix

$$\begin{bmatrix} \text{Var}[\underline{e}_{x_1}(k/k)] & 1/k \sum_{j=1}^k [\underline{e}_{x_1}(j/j)][\underline{e}_{x_3}(j/j)] \\ & -[\bar{\underline{e}}_{x_1}(k/k) \cdot \bar{\underline{e}}_{x_3}(k/k)] \\ 1/k \sum_{j=1}^k [\underline{e}_{x_1}(j/j)][\underline{e}_{x_3}(j/j)] & \text{Var}[\underline{e}_{x_3}(k/k)] \\ -[\bar{\underline{e}}_{x_1}(k/k) \cdot \bar{\underline{e}}_{x_3}(k/k)] & \end{bmatrix}$$

V. TARGET TRACKING AND ERROR ELLIPSE ANALYSIS

A. LINEAR TRACKING

Track 1 depicts a target approaching at a constant velocity of 223.6 feet per second. The solid line of Figure 5.1 indicates the true track of the target and the numbers along the track indicate the time in seconds. The target was tracked in a measurement noise, $\sigma_v = 150$, with the random forcing noise $\sigma_w = 1$. R was set for 20,000. The dots indicate the filtered track using the linear Kalman filter equations. Figures 5.2 and 5.3 are the filter error ellipses for this run, computed at increments of 10 seconds. As can be seen the ellipse size decreases with increasing time indicating filter convergence. The computed ellipse surface areas shown on the figures confirm this. Figure 5.4 shows the filtered track for the case where σ_v has been increased to 300 and all other parameters remain the same. The error ellipses of Figure 5.5 computed for 10-second increments show increasing area indicating filter divergence. Figure 5.6 shows the error ellipses for the same track run but this time the ellipses were computed using a "statistics window" of 10. By this is meant that the ellipses were derived from statistics computed for the last 10 data measurements. All previous data is disregarded. Using this

method, the ellipses of Figure 5.6 show filter convergence from iterations 15 to 25. The filtered track of Figure 5.4 confirms this. Figure 5.7 shows the results for the same track parameters, except in this case a statistics window of 5 was used. The window 5 ellipse area at time 25 (5173 sq ft) is much less than the area of either the run with the statistic window of 10 (11,540 sq ft) or the run with no window at all (65,500 sq ft). This is expected since the filter is essentially "locked on" at time 20, and the window 5 ellipse at time 25 disregards all data previous to time 20. Figure 5.8 shows the error ellipses for the same track but the measurement noise was increased to $\sigma_v = 400$, while R was kept at 20,000. The error ellipses indicate filter divergence, and indeed the filtered track headed off in the wrong direction.

Track 2 depicts a target approaching at a constant speed of 500 feet per second in the -y direction. Figure 5.9 depicts the solid line track and the dots indicate the linear filtered track with $\sigma_v = 150$, $\sigma_w = 1$ and $R = 20,000$. Figure 5.10 and 5.11 are the error ellipses for the run. No statistics window was used. Other than the fact that the ellipse area is decreasing, the shape of the ellipse provides little additional information. Figure 5.12 and 5.13 show the ellipses for the normalized error. With the same measurement noise sigma for both the x-position and y-position measurements, the normalized error ellipse's shape and orientation reflect

the target track proximity to either axis. In Figure 5.12 the ellipse major axis indicates a large normalized error in the x-direction. This is to be expected since the target maintains a constant x-position of 500 feet, while the y-position is initially 20,000 feet. However, near time 40 as the target approaches the x-axis, the normalized y error increases and becomes so large at the x-axis crossing that the normalized x error becomes insignificant in comparison. This can be seen in Figure 5.13 for the ellipses at time 45 and 55 compared with the ellipse at time 35. The normalized error ellipse is an excellent indicator of target proximity to an axis, but the rapid shifts in ellipse surface area make it difficult to determine filter convergence.

Track 3 depicts a target approaching on a parabolic track at a speed of 200 feet per second. Figure 5.14 is the true track, with a linearly filtered track indicated by the dots. For this run $\sigma_v=150$, $\sigma_w=10$, and $R=20,000$. Figure 5.15 are the error ellipse plots for times 40, 50, and 60, the period of the highest rate of change in x- and y-velocity. The ellipse areas increase with time indicating divergence. Figure 5.16 and 5.17 are the ellipse plots using a 10-data point and a 5-data point statistics window respectively. In both cases the ellipse areas for time 60 are less than time 50 indicating the filter has tracked around the curve.

Using error ellipses based on a statistics window in this tracking situation provides a better indicator of filter performance.

For the second run of track 3, σ_y was increased to 300 and all other parameters remained the same. Figure 5.18 shows the resulting filtered track, which obviously didn't track around the curve. With the large amount of measurement noise and considering that the maximum random forcing input, i.e. the maximum acceleration in the x- and y-direction, occurs between times 40 and 60, it is a logical place to lose track. Another factor to be considered is the decrease in gain as k increases. By time 40 the gains have little influence. So a system was incorporated in the program to "reinitialize" the filter by setting the gains to $G(0)$, if certain conditions were met. After several trial and error runs, it was determined that if a statistics window of 10 were used, and the gains reinitialized if the error ellipse area increased consecutively a certain number of times, that the filtered track would follow around the curve. Figure 5.19 is the filtered track using a statistics window of 10 and reinitializing the filter if the error ellipse area increased consecutively during five 1-second increments. The error ellipses for that run are shown in Figures 5.20 and 5.21. As indicated on the figures, the filter was reinitialized four times and the ellipse areas for the 10-second increments increased, until reinitializing the

filter at time 52 locked the filter in. Consequently the error ellipse areas for time 60 and 70 decreased, indicating convergence.

In the final run, the filter was reinitialized after 10 consecutive 1-second error ellipse increases, with all other parameters remaining the same. Figure 5.22 is the filtered track; Figures 5.23 and 5.24 are the error ellipse plots for this run. As indicated on Figure 5.24 the filter was reinitialized only once at time 57. A comparison of ellipse areas for the last two runs shows that, with the exception of time 70, the areas were larger in the first run when the filter was reinitialized 4 times. This is expected since reinitializing results in larger gains producing more widely vary estimates, and hence greater error variance. At time 70 the error ellipse area of the first run is less since in the first run the last filter reinitialization occurred at time 52 versus time 57 in the second run. The first filtered track had more time to settle out by time 70, resulting in less error.

B. NONLINEAR TRACKING

Track 4 depicts a target moving at a constant velocity of 50 feet per second (30 kts) in the x-direction for 15 seconds, at which time the target turns and travels in the -y-direction. (See Figure 5.25) Using the extended Kalman filter with $\sigma_y=30$ and $R=900$, a series of tracking runs were

made for various values of COVW (σ_w^2 =from 20 to 200). In none of these runs did the filter successfully track the target around the turn. Figure 5.26 shows the results for the case when COVW=150. In this instance the filter lost track as the target came out of the turn. Trying to track through a turn using a constant COVW (and hence, a constant Q) did not work. So a scheme was devised to vary COVW dependent on information derived from the error ellipse. After several trial runs for this particular track, it was determined that if the error ellipse area increased consecutively for 7 iterations of k , COVW would be doubled, and if the ellipse area decreased consecutively for 5 iterations of k , COVW would be halved. Initially the the trial runs were made without a statistics window, and the filter did not track successfully. Without the statistics window, the old data weighted down the statistics, and the error ellipses were not indicative of what was currently happening. So it was decided to use a statistics window. Windows of 5, 10, and 15 were tried. Window 5 proved to be too responsive and window 15 not responsive enough. So a statistics window of 10 was chosen for the tracking run. With $P_0=10^2$, $\sigma_v=30$, $R=900$, and COVW initially set at 20, the tracking run was made. Figure 5.27 depicts the filtered track output, and Figures 5.28-5.30 are the 10-second incremental error ellipses for the run. As can be seen, the filter did track around the curve. Figure 5.29 shows the ellipse areas are becoming less between times 55 and 65. Also indicated below the plots are the values of

COVW for the k time the plot was computed. During this particular run COVW varied from an initial value of 20 up to 160, and then decreased to 40 by the end of the run.

Using the same filter parameters as above except σ_v was increased to 200, and R to 40,000, another run was made. The filter did not track at all. During this run COVW varied from an initial value of 20 up to 40 and decreased to 5 by the end of the run. Obviously, the criteria for increasing and decreasing COVW was not effective. More trial runs were necessary to determine the optimum consecutive increases or decreases of the ellipse areas before adjusting COVW accordingly.

A second approach to the nonlinear tracking problem, one that was used earlier for the linear case, is to reinitialize the filter if certain conditions are met. Again, using trail and error runs with and without statistics windows, it was determined that using a statistics window of 10 gave the best results. Using initial conditions of COVW=150, $P_0=10^2$, $\sigma_v=30$, and $R=900$, several runs were made, reinitializing the filter if the error ellipse area increased consecutively for a certain number of iterations of k . Of the runs attempted, the best results were obtained when the filter was reinitialized if the area increased for 5 consecutive iterations of k . Figure 5.31 is the filtered track for this run, and Figures 5.32-5.34 are the error ellipse plots. Indicated below the plots are the times, k , when the filter

was reinitialized. For this particular run the filter was reinitialized 5 times. It should be noted that when reinitializing the filter, $\underline{P}(k/k-1)$ was reset to $10^2 \times \underline{P}_0$. \underline{P}_0 was not large enough to be effective in getting the filter back on track. The initial value of 10^2 was used for \underline{P}_0 to reflect the high confidence in the initial state conditions. Other values of \underline{P}_0 did not work as well.

Using the same parameters as above except the filter was reinitialized after 7 consecutive error ellipse area increases, another run was made with the resulting track depicted in Figure 5.35. A comparison with Figure 5.31 reveals that using 7 area increases as the criterion for filter reinitialization resulted in poorer filter performance, as can be shown from the error ellipses.

The final nonlinear filter tracking runs attempted involved simultaneously varying COVW and filter reinitialization. The results were disastrous, and highly unpredictable. It was an interesting experiment in futility, and no meaningful results could be obtained.

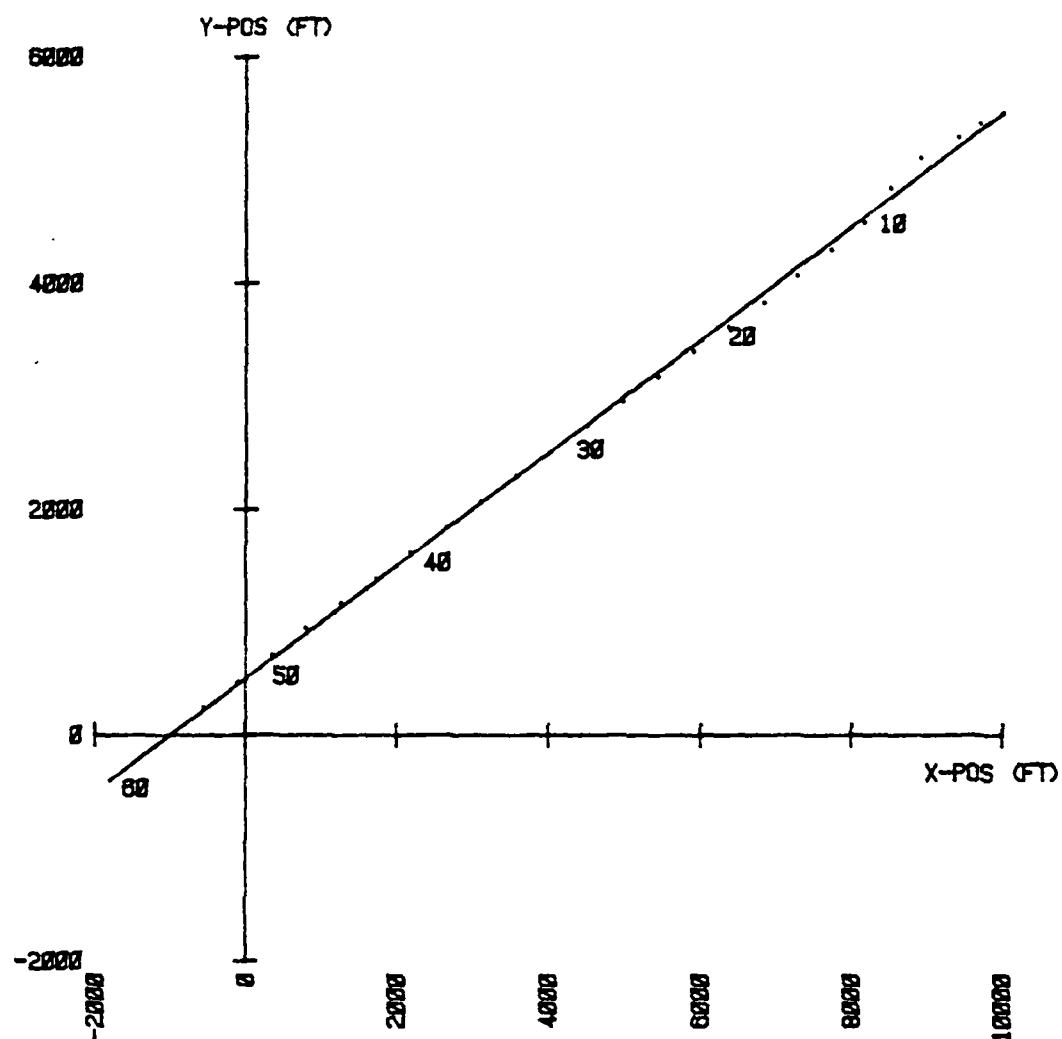
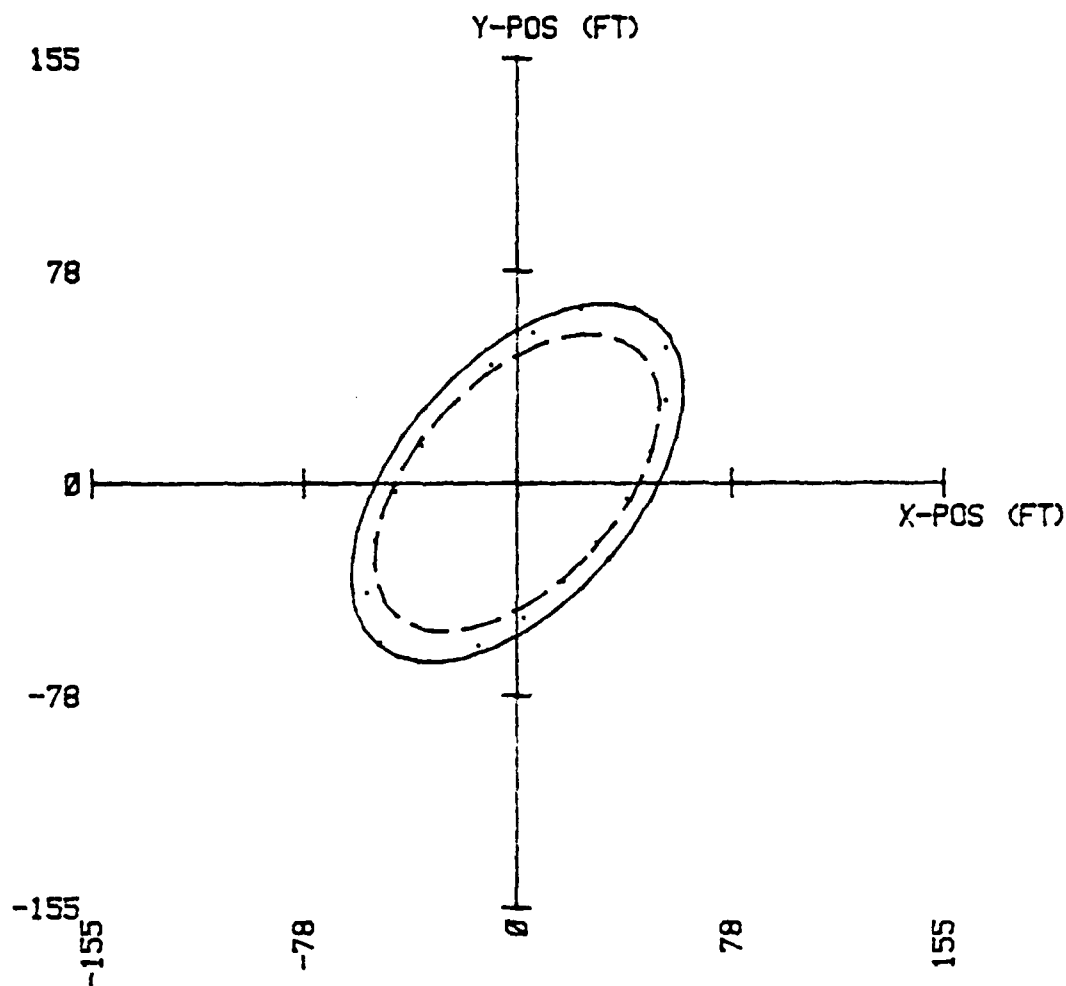


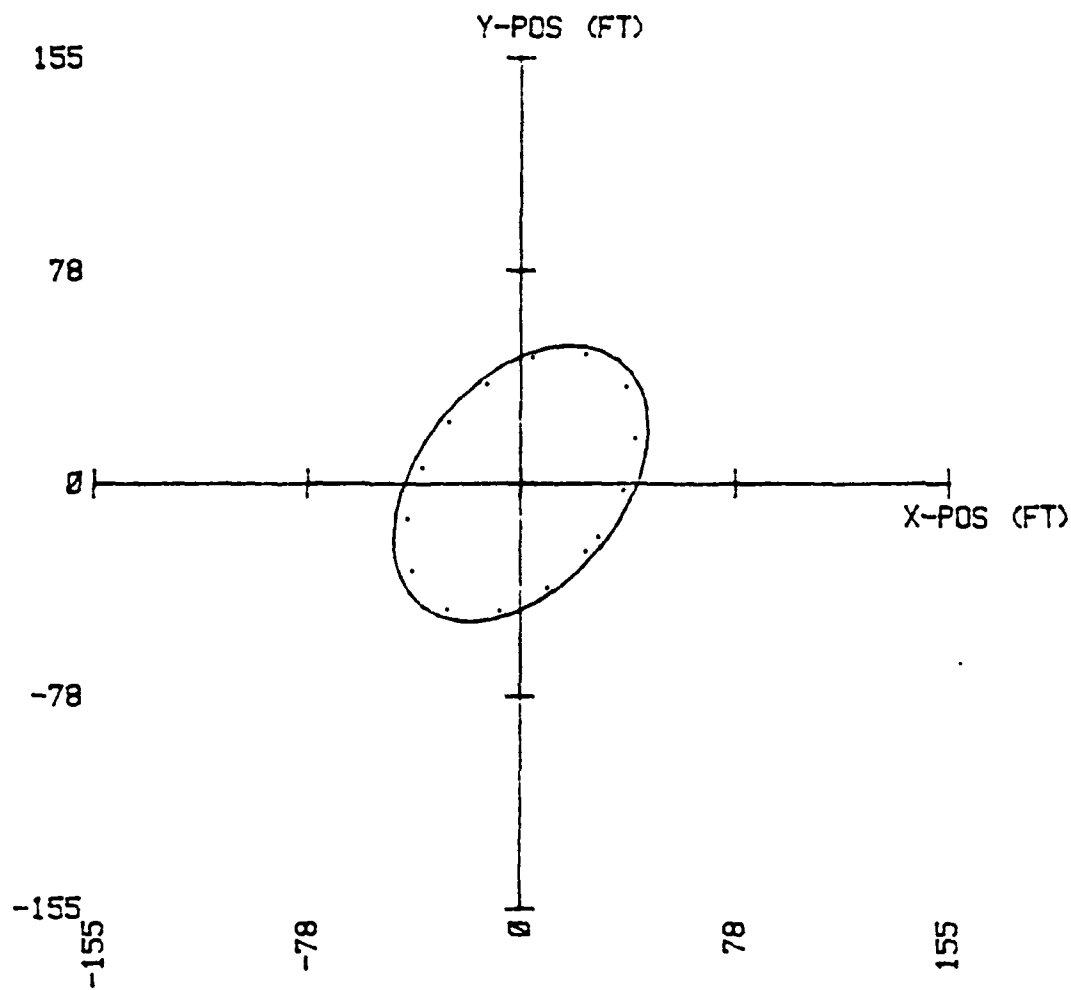
Figure 5.1 Solid Line Track 1, Vel 223.6 ft/sec; Dots
Indicate Filtered Track, $\sigma_v=150$, $\sigma_w=1$, $R=20,000$



COVW=1 SIGV=150 R=20000 TIME AREA(SQ FT) LEG

10	1057E+001	—
20	8790E+000
30	7540E+000	- - -

Figure 5.2 Filtered Track 1 Error Ellipses at 10 Second Increments, $\sigma_v=150$



COVW=1	SIGV=150	R=20000	TIME AREA (SQ FT)	LEG
			40 6681E+000	—
			50 5741E+000

Figure 5.3 Filtered Track 1 Error Ellipses at 10 Second Increments, $\sigma_v=150$

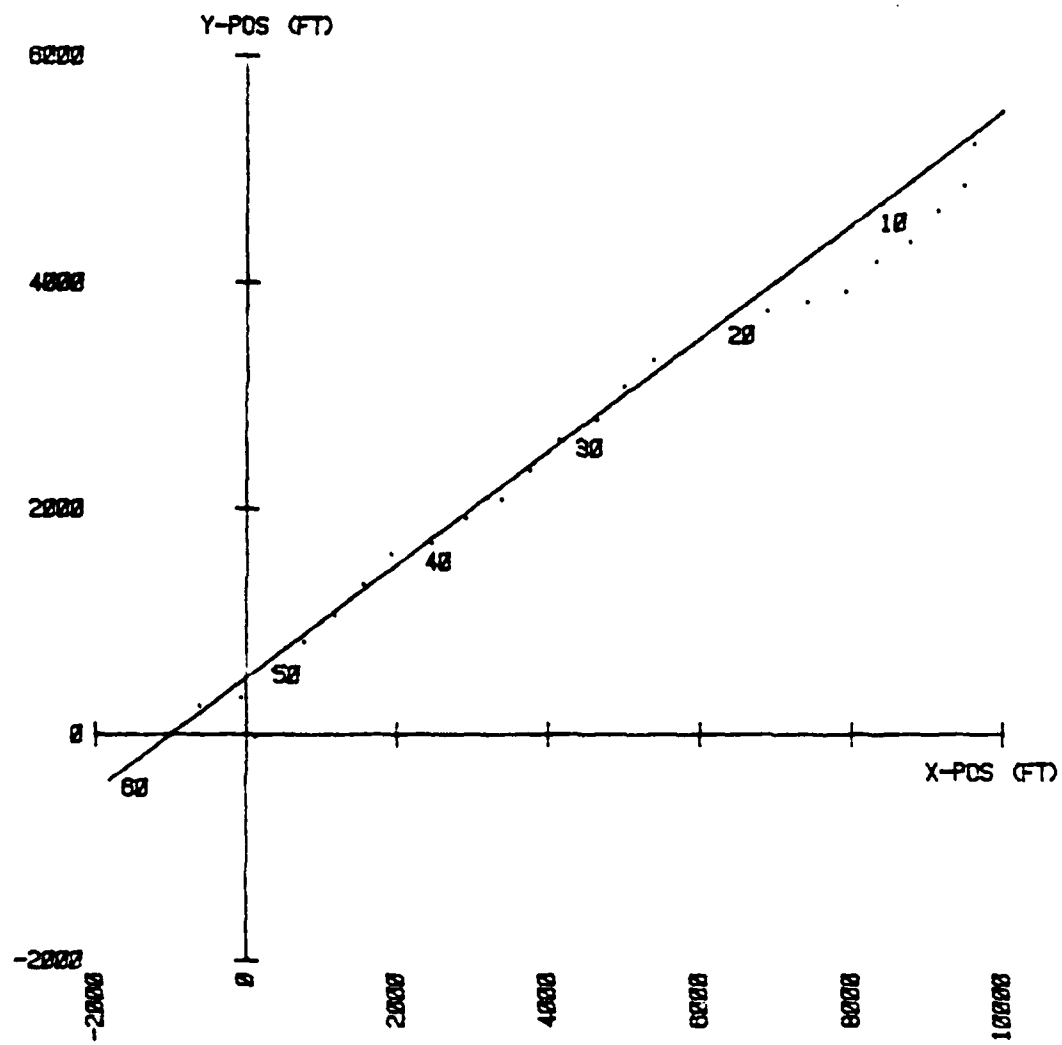
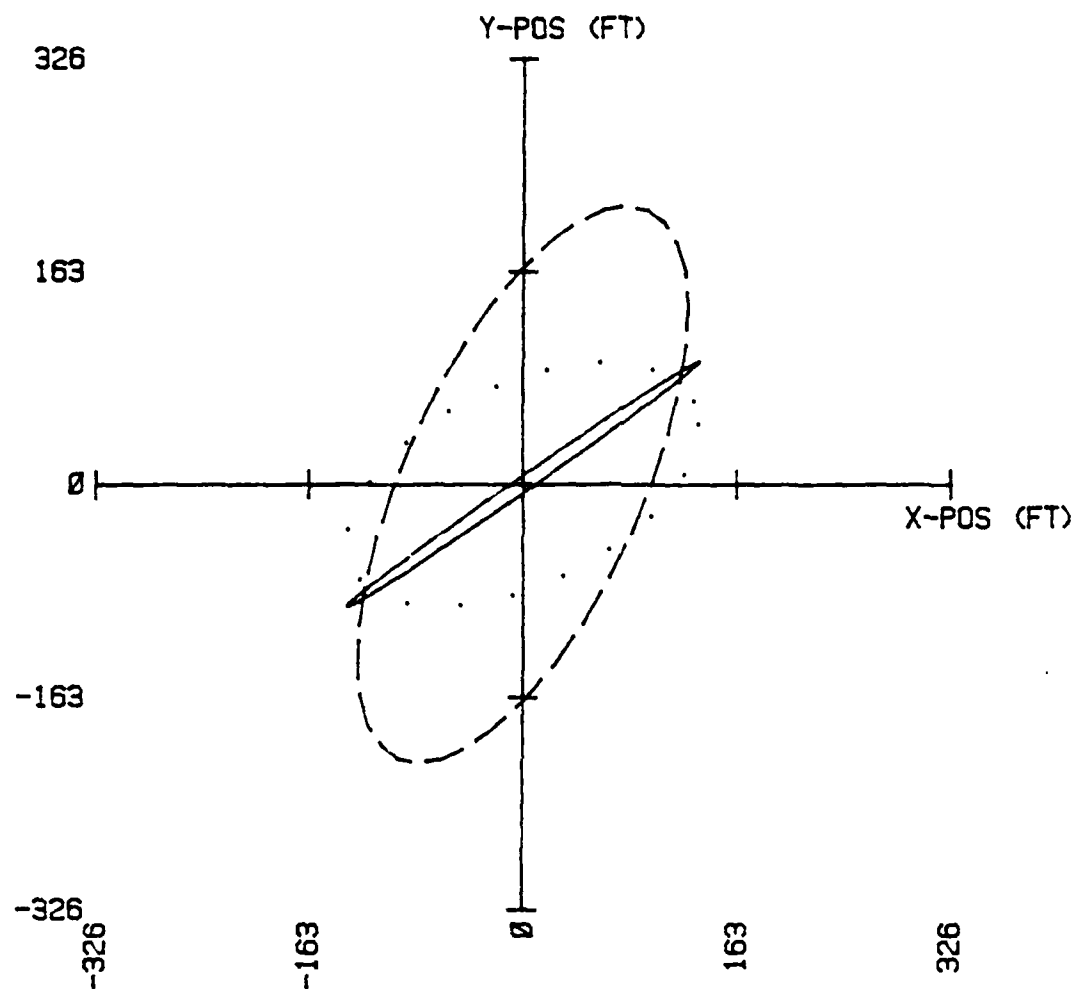


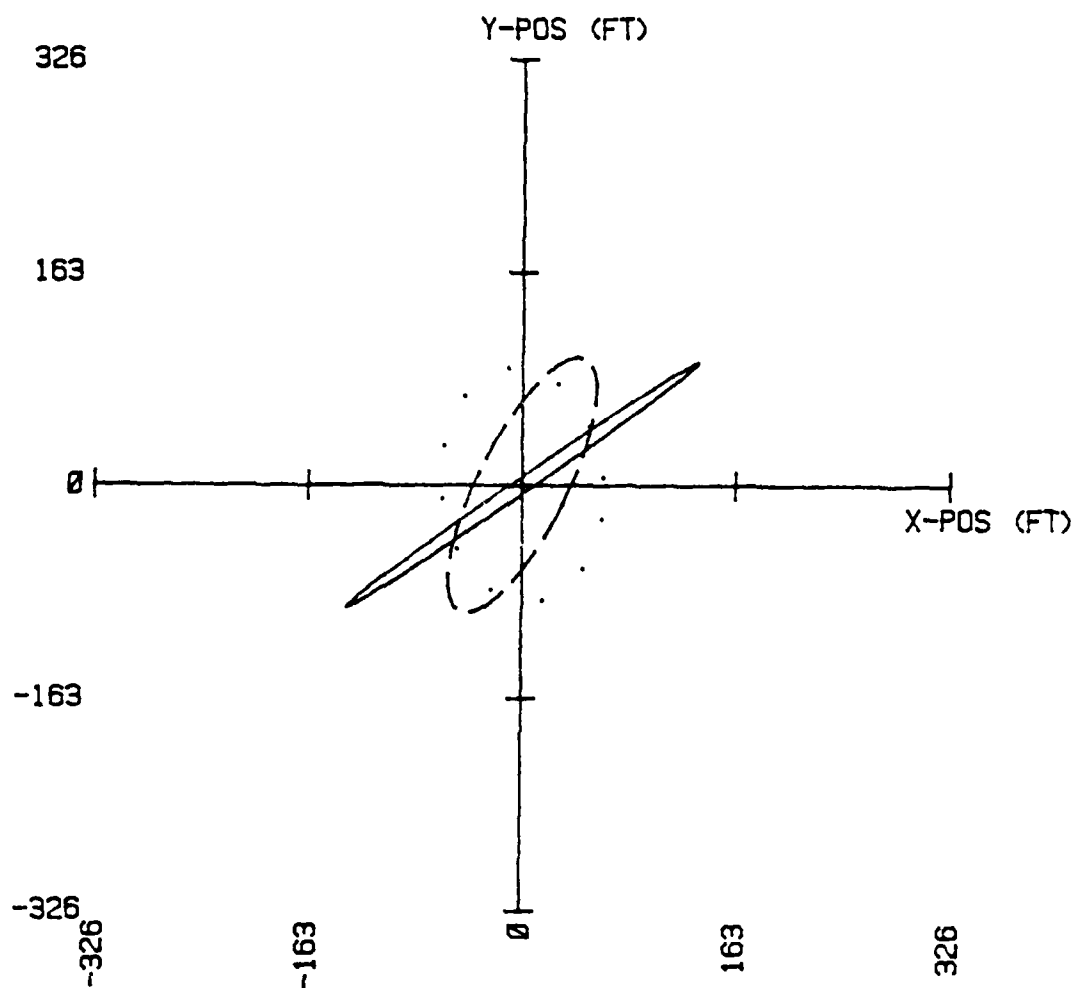
Figure 5.4 Filtered Track 1, $\sigma_v=300$, $\sigma_w=1$, $R=20,000$



COVW=10 SIGV=300 R=20000 TIME AREA (SQ FT) LEG

5	2858E+000	—
15	3480E+001
25	6550E+001	- - -

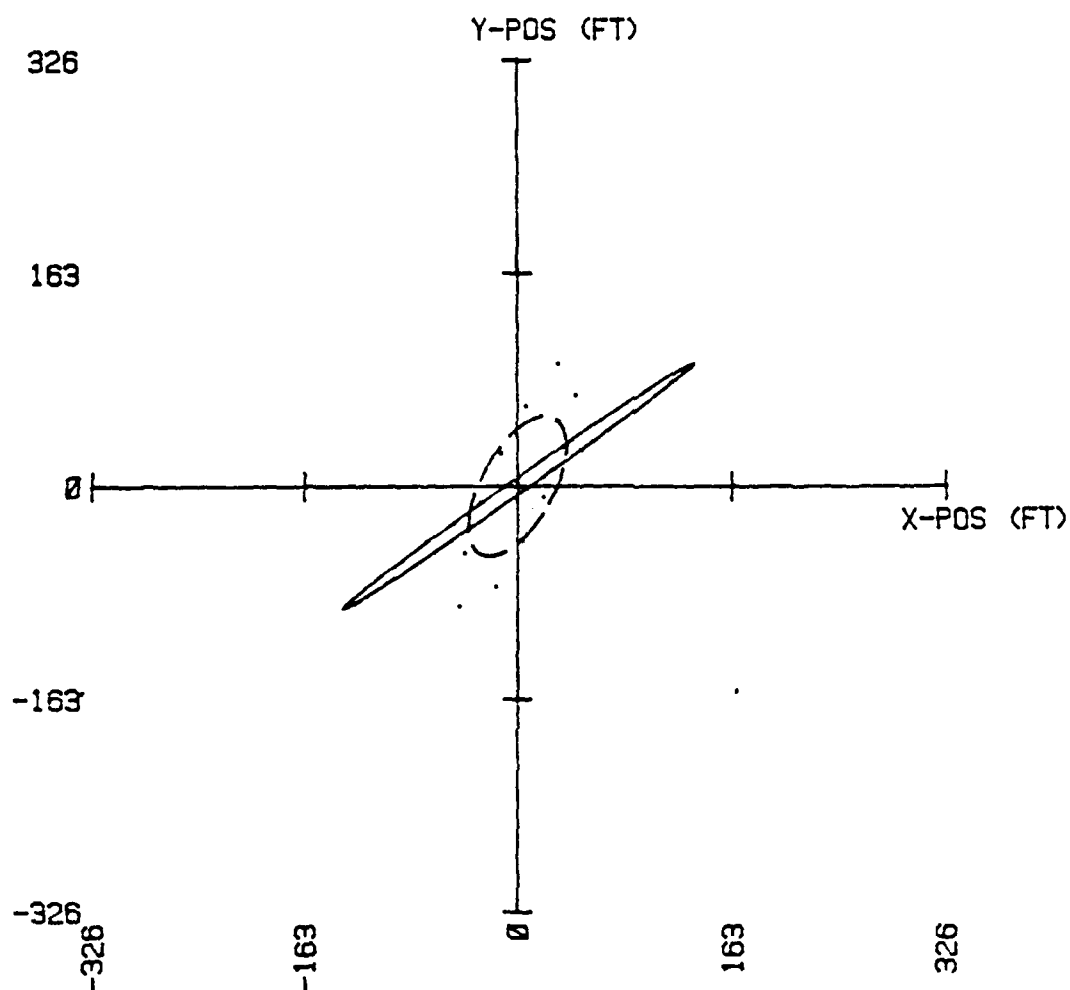
Figure 5.5 Filtered Track 1 Error Ellipses for $\sigma_y = 300$



COVW=10 SIGV=300 R=20000 TIME AREA(SQ FT) LEG

5	2858E+000	—
15	1745E+001
25	1154E+001	- - -

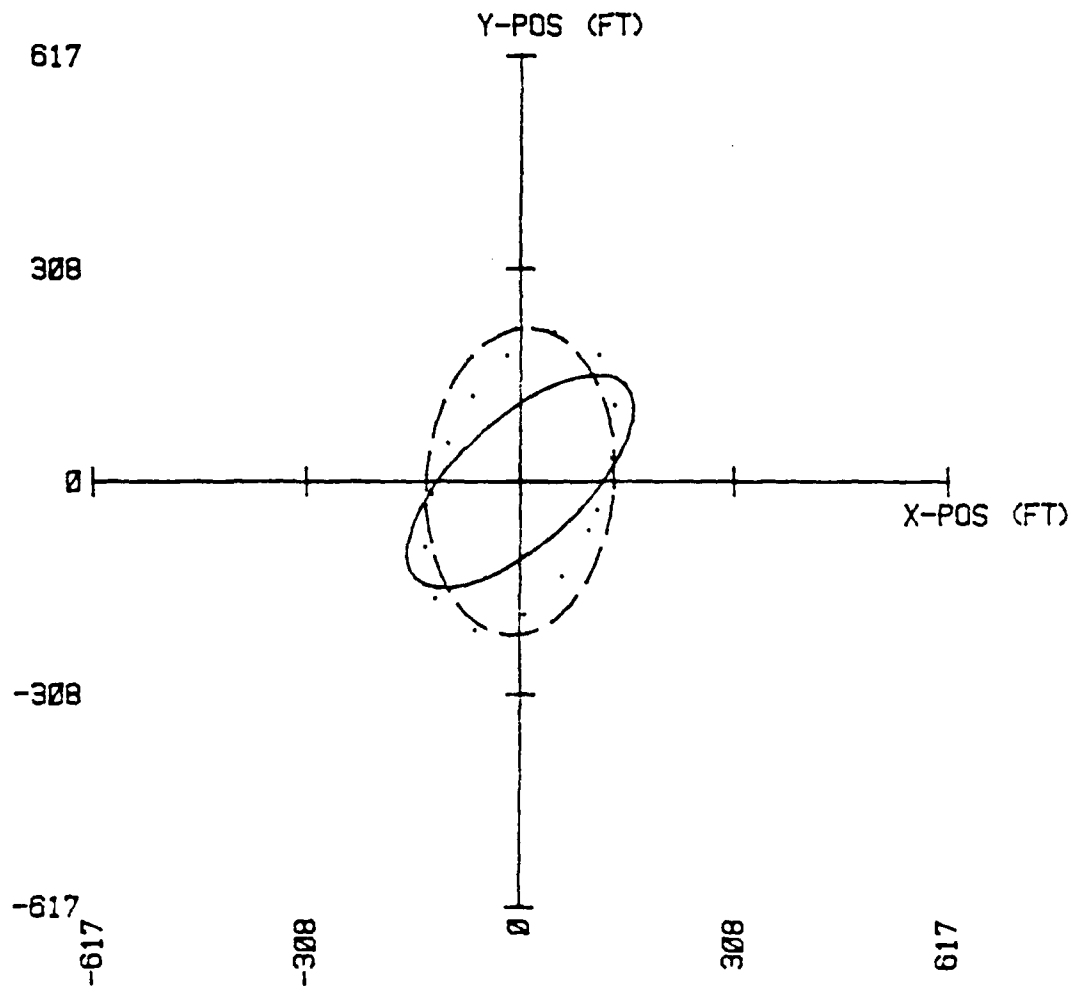
Figure 5.6 Filtered Track 1 Error Ellipses for $\sigma_v=300$,
Using Statistics Window of 10



COVW=10 SIGV=300 R=20000 TIME AREA (SQ FT) LEG

5	2858E+000	—
15	7225E+000
25	5179E+000	- - -

Figure 5.7 Filtered Track 1 Error Ellipses for $\sigma_v=300$,
Using Statistics Window of 5



COVW=10 SIGV=400 R=20000 TIME AREA(SQ FT) LEG

5	5825E+001	—
9	8489E+001
13	9507E+001	- - -

Figure 5.3 Filtered Track 1 Error Ellipse for $g_y=400$

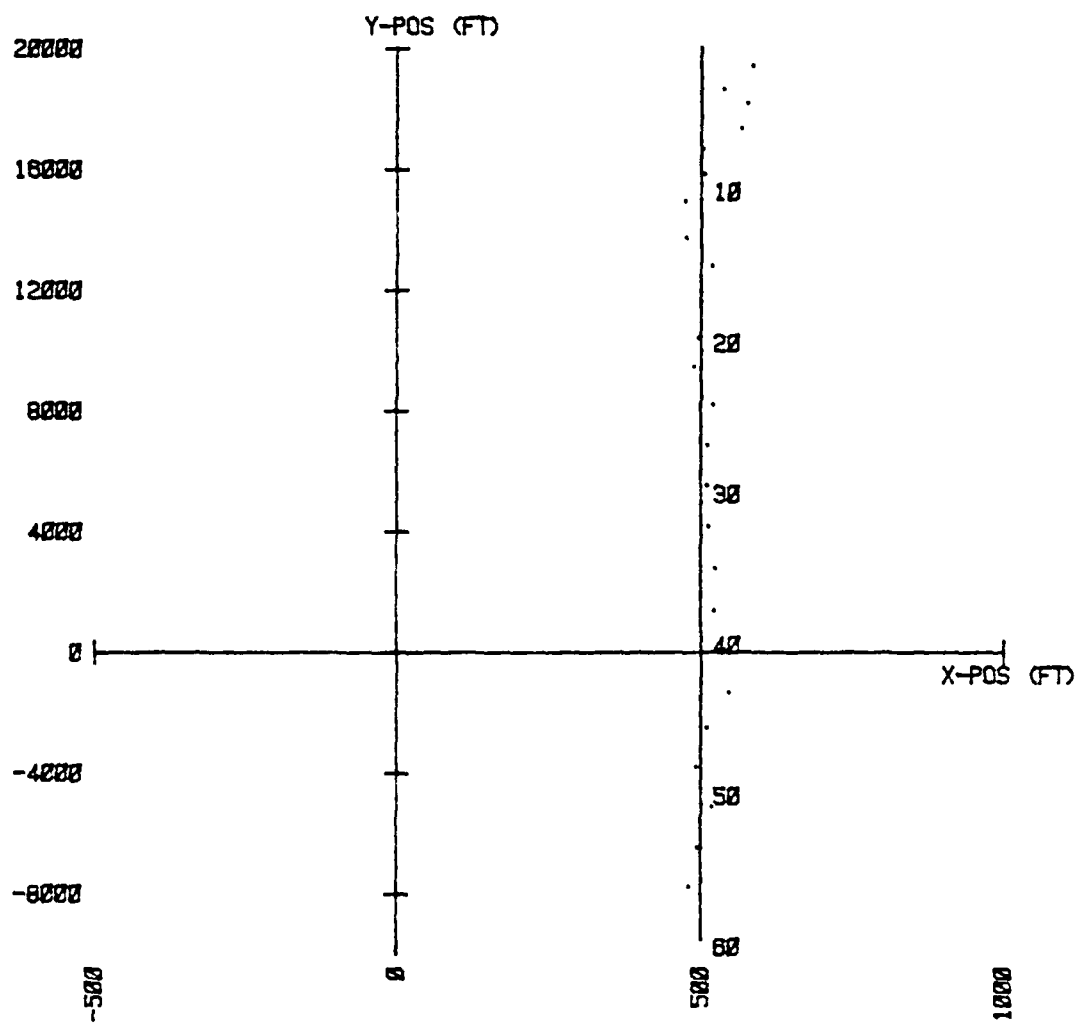
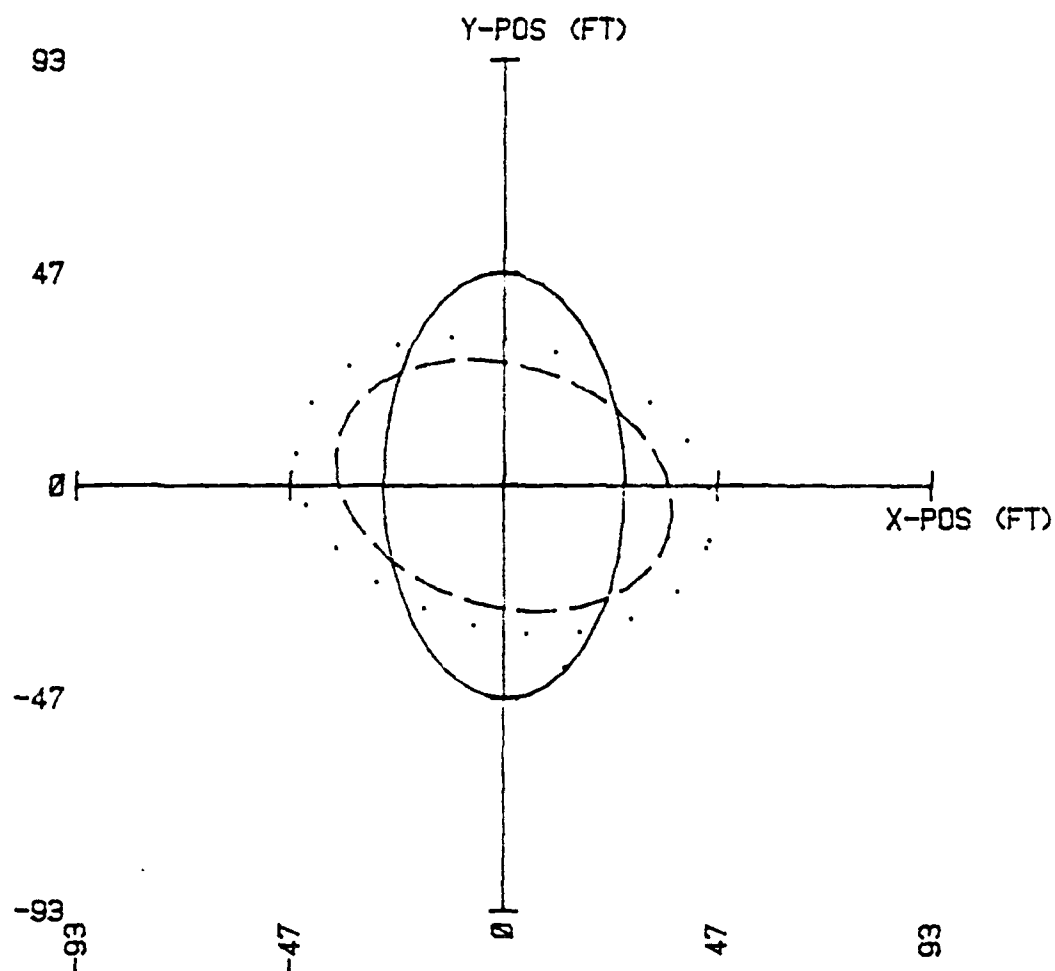
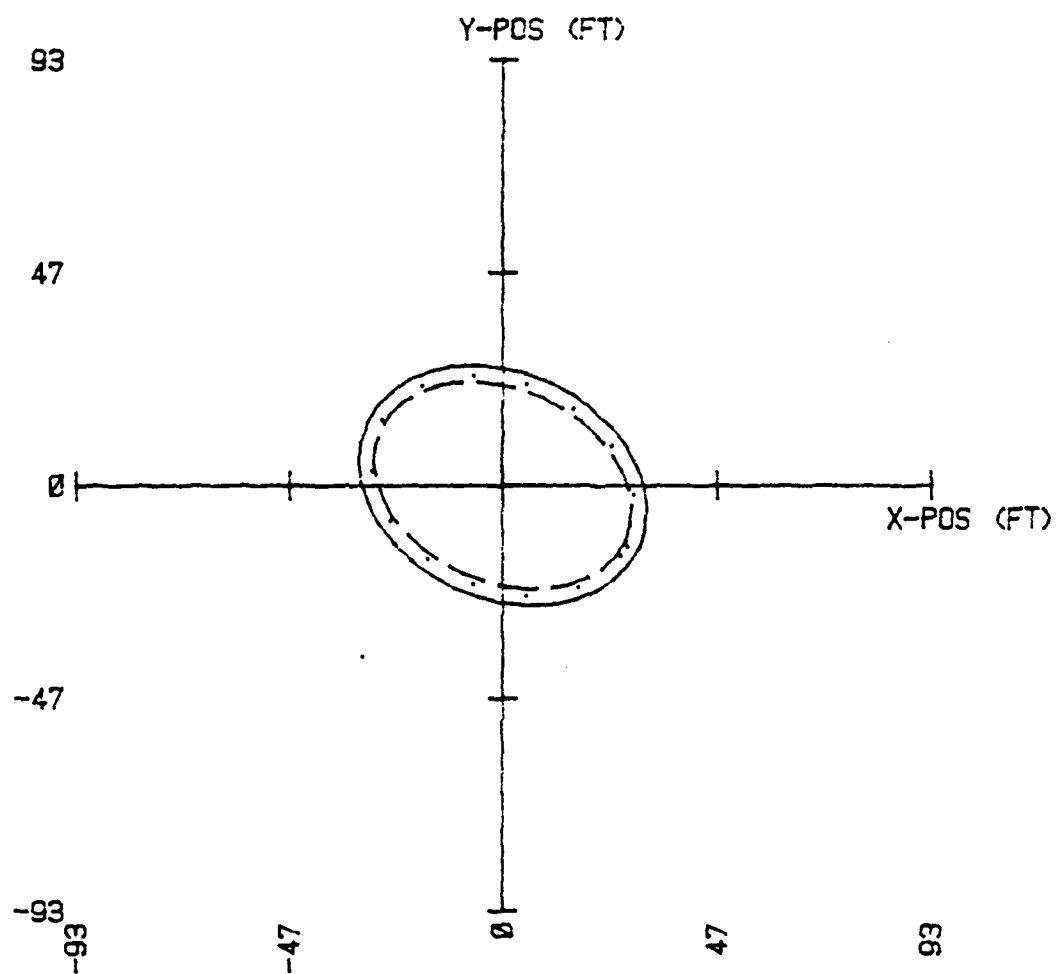


Figure 5.9 Solid Line Track 2, Vel 500 ft/sec, Dots Indicate Filtered Track for $\sigma_y=150$, $\sigma_w=1$, $R=20,000$



COVW=1	SIGV=150	R=20000	TIME	AREA (SQ FT)	LEG
			5	3868E+000	——
			15	4604E+000
			25	3132E+000	- - -

Figure 5.10 Filtered Track 2 Error Ellipses, $\sigma_y=150$



COVW=1 SIGV=150 R=20000 TIME AREA (SQ FT) LEG

35 2550E+000 ———

45 2137E+000

55 1950E+000 - - -

Figure 5.11 Filtered Track 2 Error Ellipses, $\sigma_v=150$

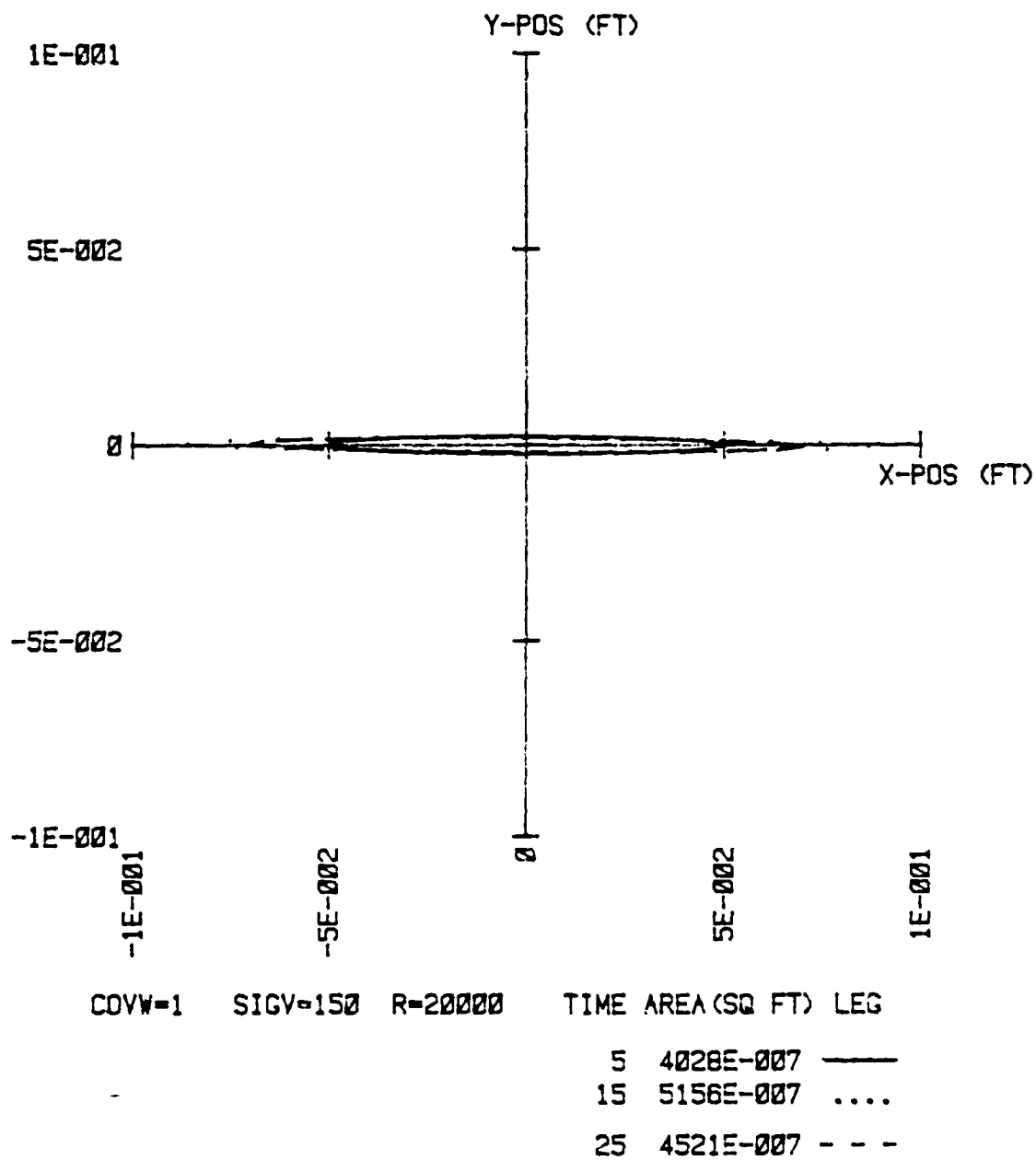


Figure 5.12 Filtered Track 2 Error Ellipses, $\sigma_y=150$, Error Normalized

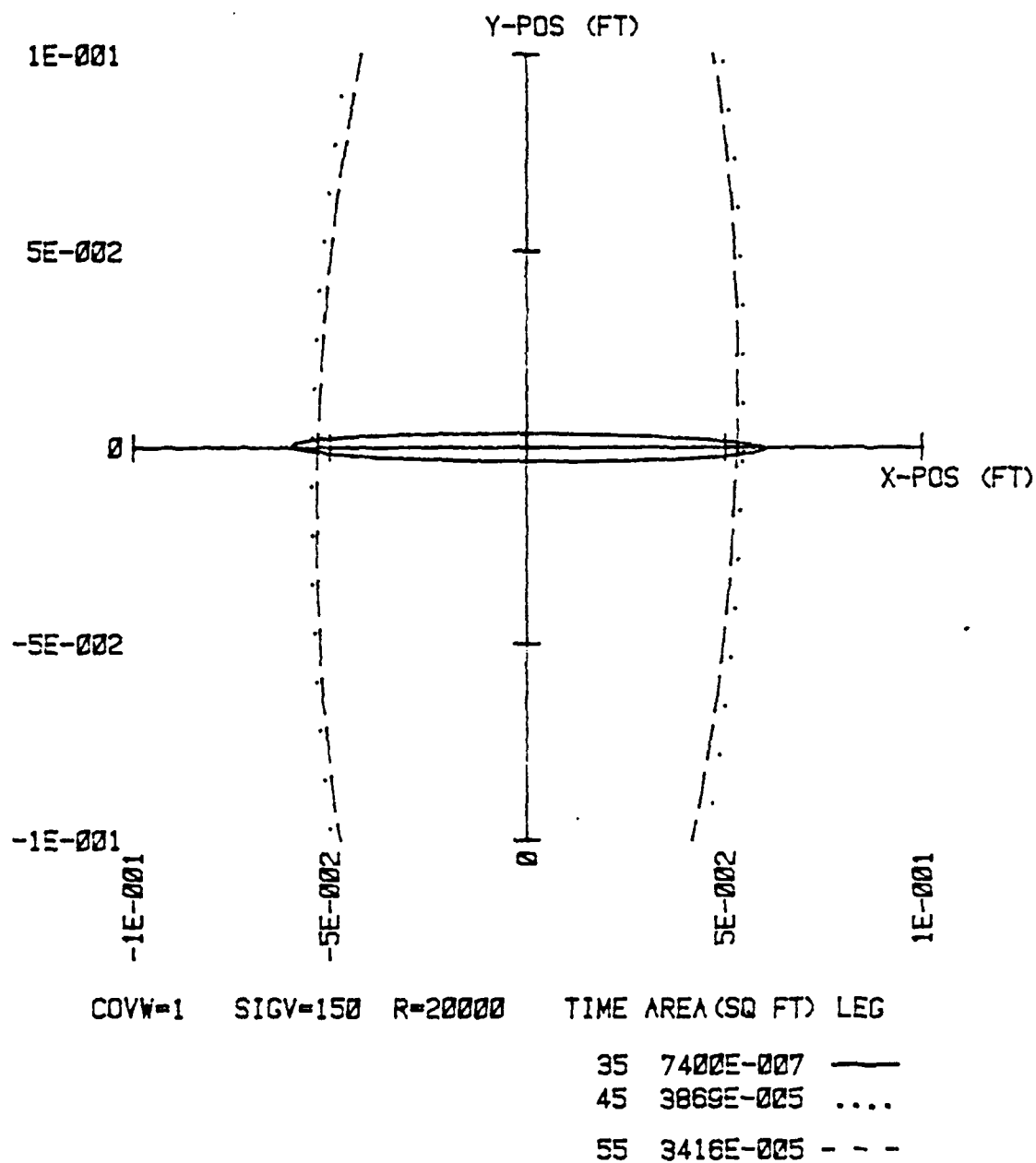


Figure 5.13 Filtered Track 2 Error Ellipses, $\sigma_v=150$, Error Normalized

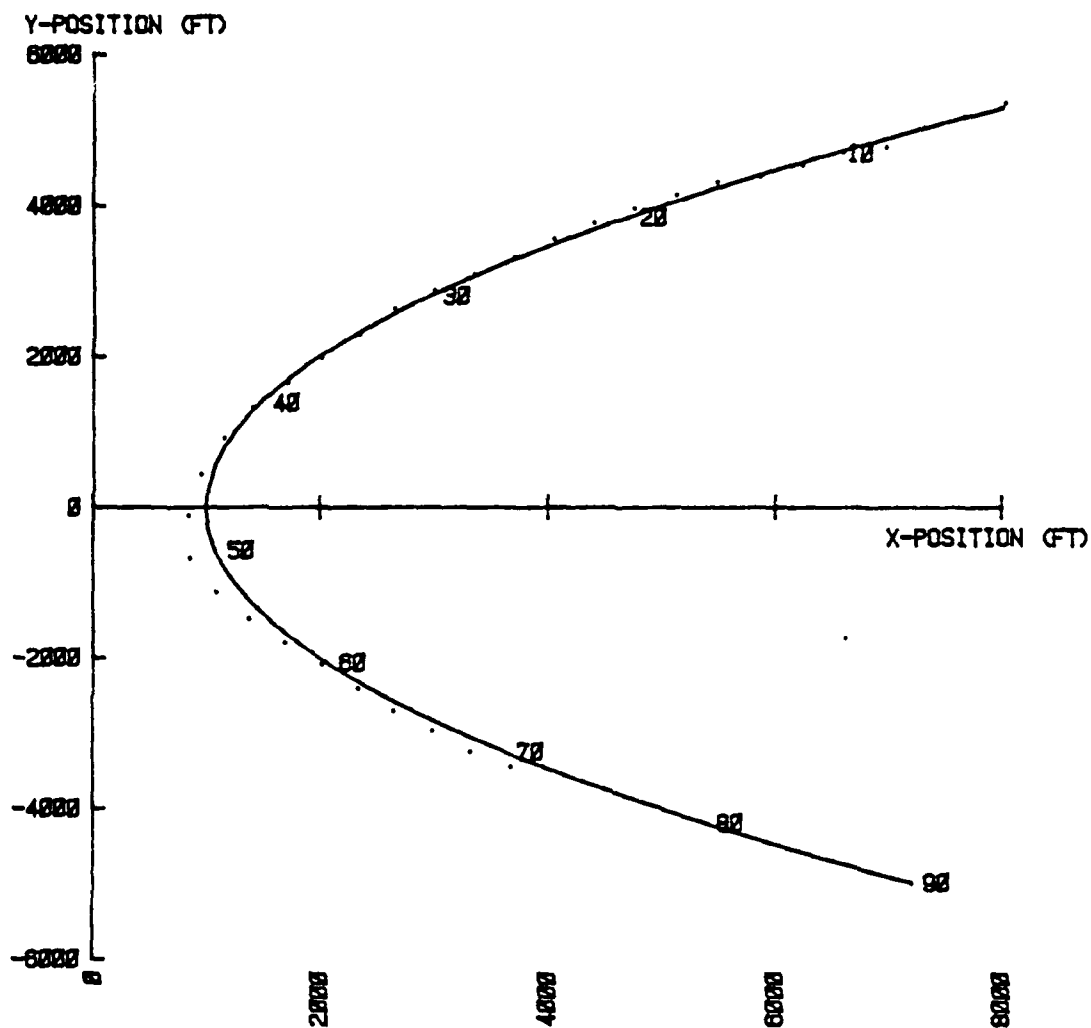
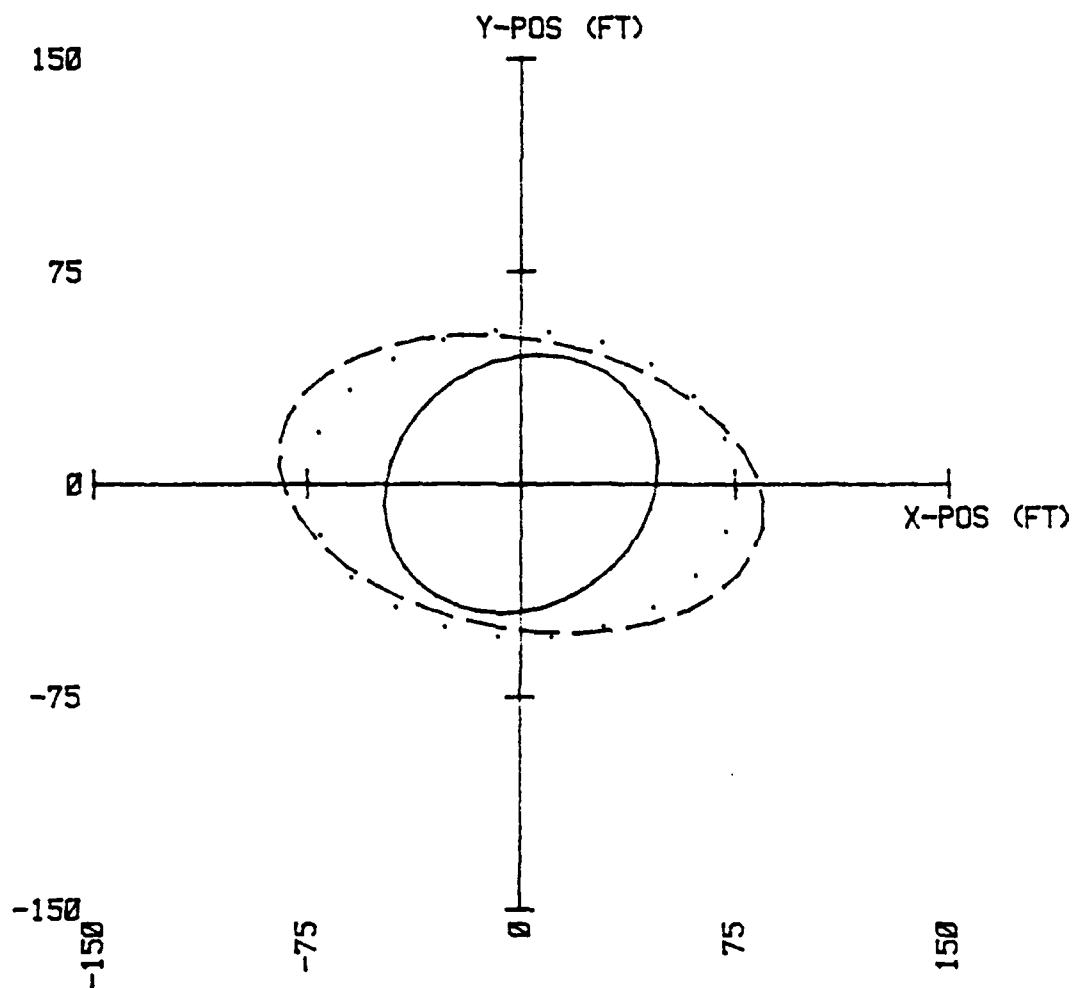


Figure 5.14 Solid Line Track 3, Vel 200 ft/sec, Dots
Indicate Filtered Track for $\sigma_v=150$, $\sigma_w=10$,
 $R=20,000$



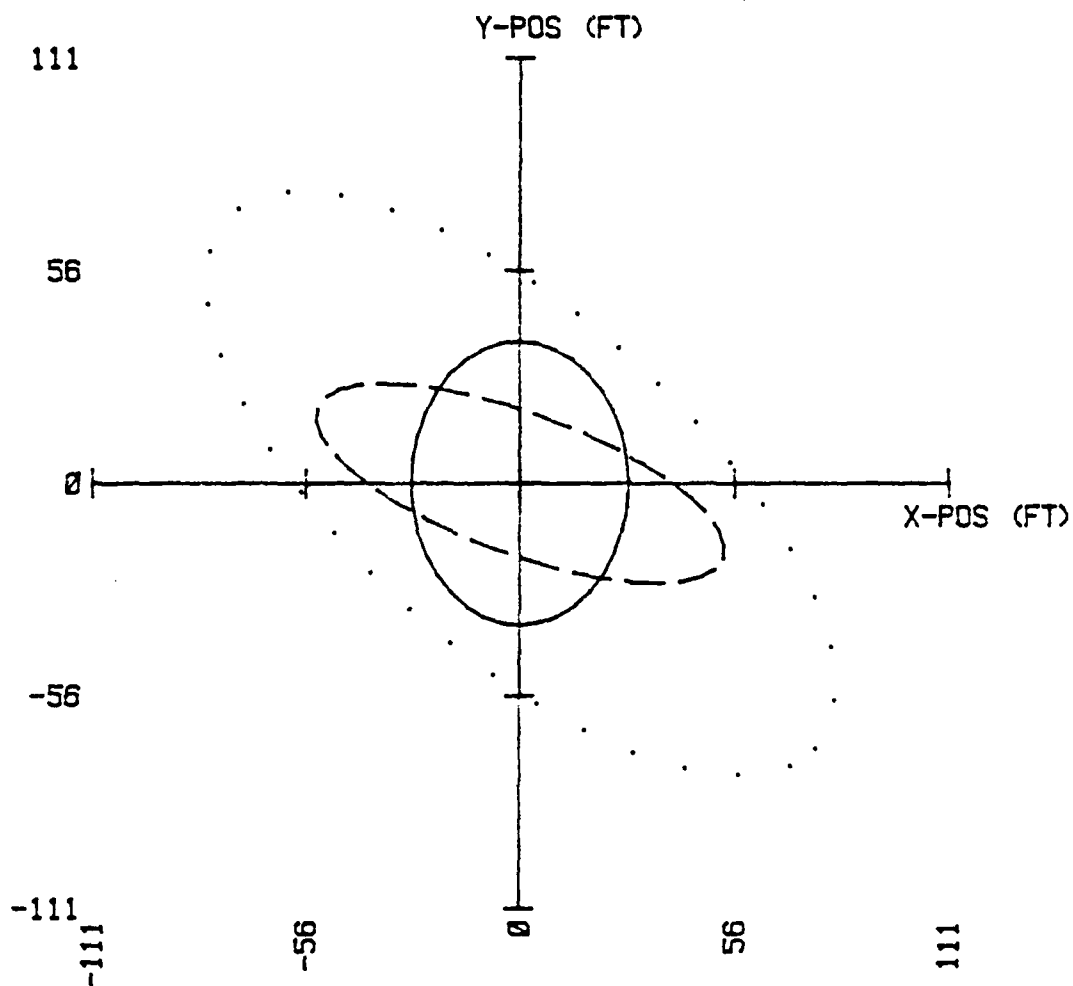
COVW=100 SIGV=150 R=20000 TIME AREA(SQ FT) LEG

40 6814E+000 ———

50 1291E+001

60 1388E+001 - - -

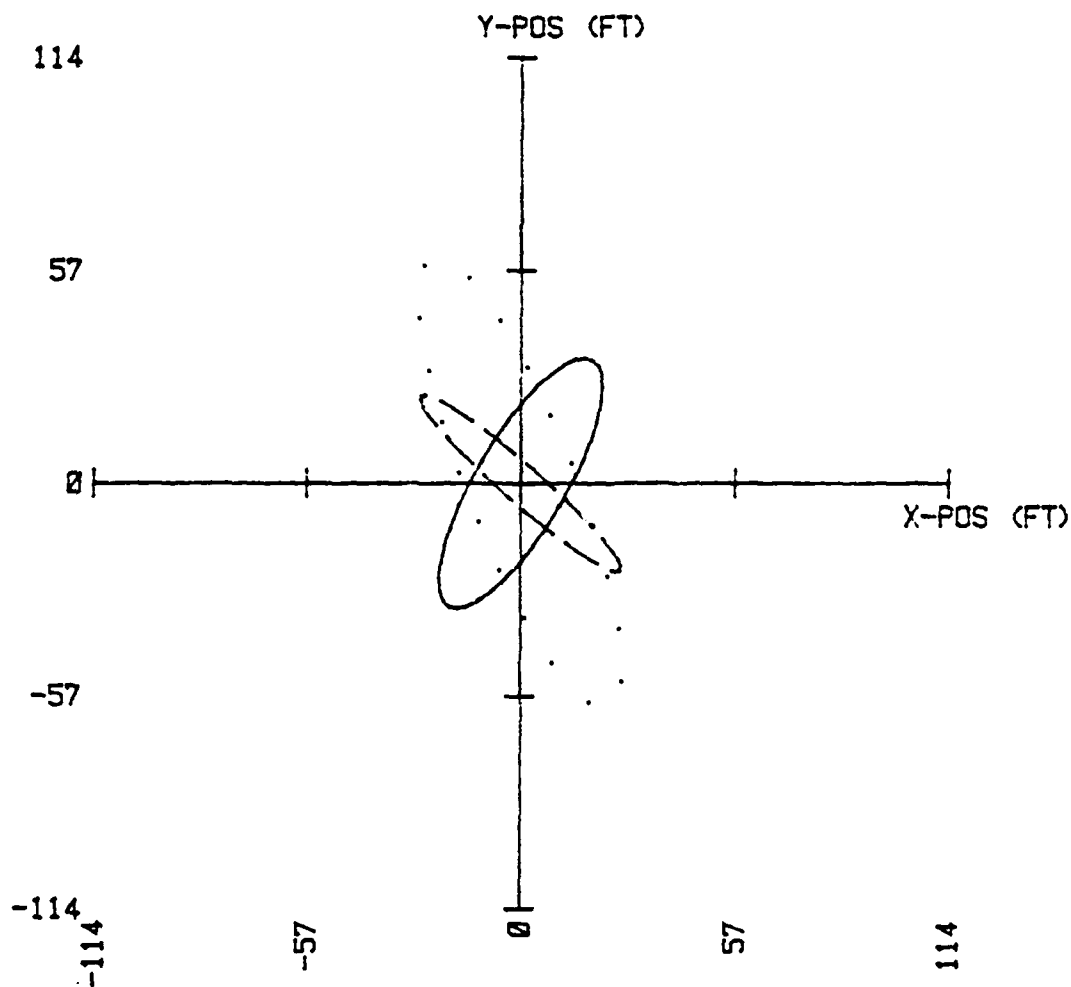
Figure 5.15 Filtered Track 3 Error Ellipses, $\sigma_y=150$



COVW=100 SIGV=150 R=20000 TIME AREA (SQ FT) LEG

40	3284E+000	—
50	1420E+001
60	3257E+000	- - -

Figure 5.16 Filtered Track 3 Error Ellipses, $\sigma_y=150$,
Statistics Window 10



COVW=100 SIGV=150 R=20000 TIME AREA (SQ FT) LEG

40	1448E+000	—
50	2945E+000
60	5517E+001	- - -

Figure 5.17 Filtered Track 3 Error Ellipses, $\sigma_v=150$,
Statistics Window 5

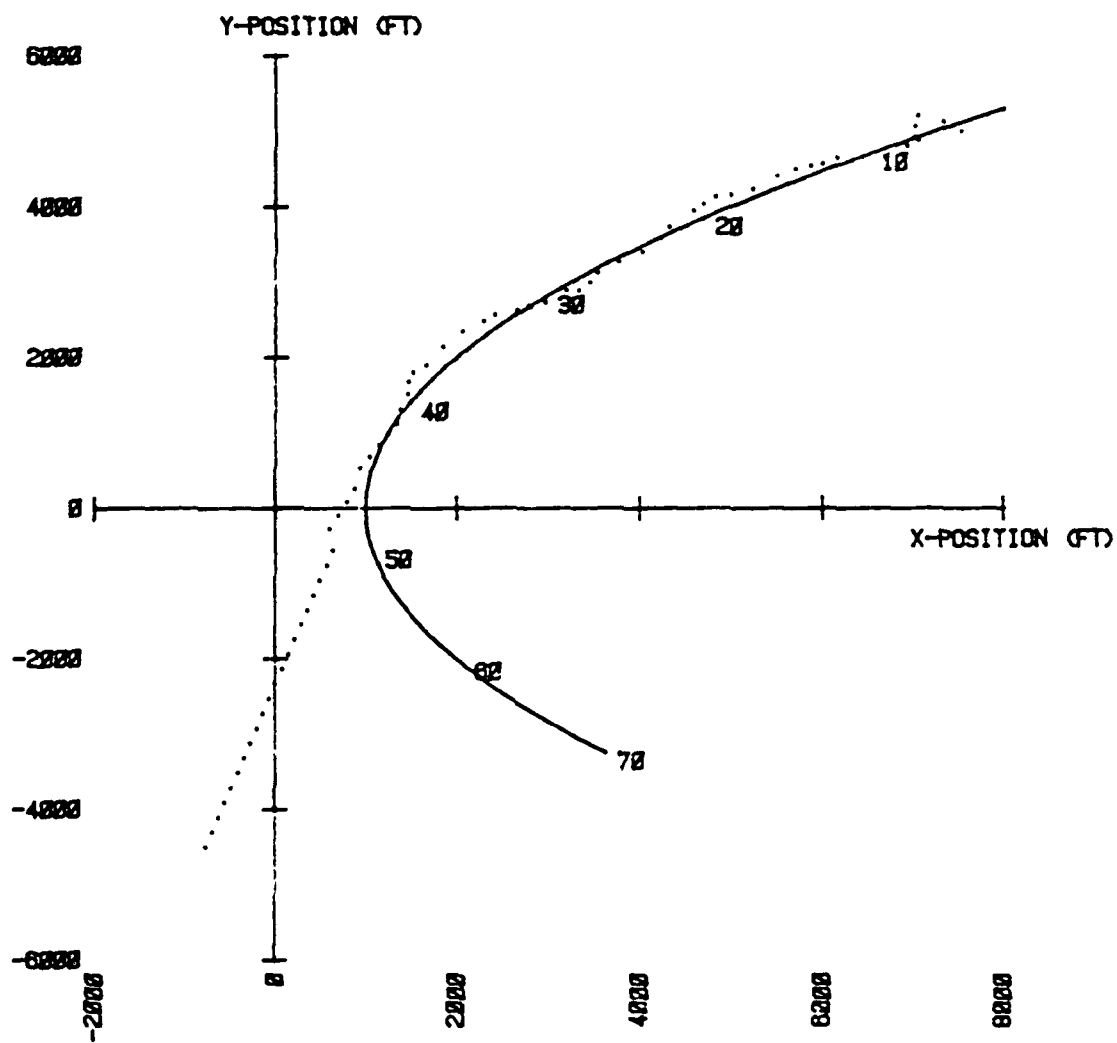


Figure 5.18 Filtered Track 3 for $\sigma_v=300$, $\sigma_w=10$, $R=20,000$

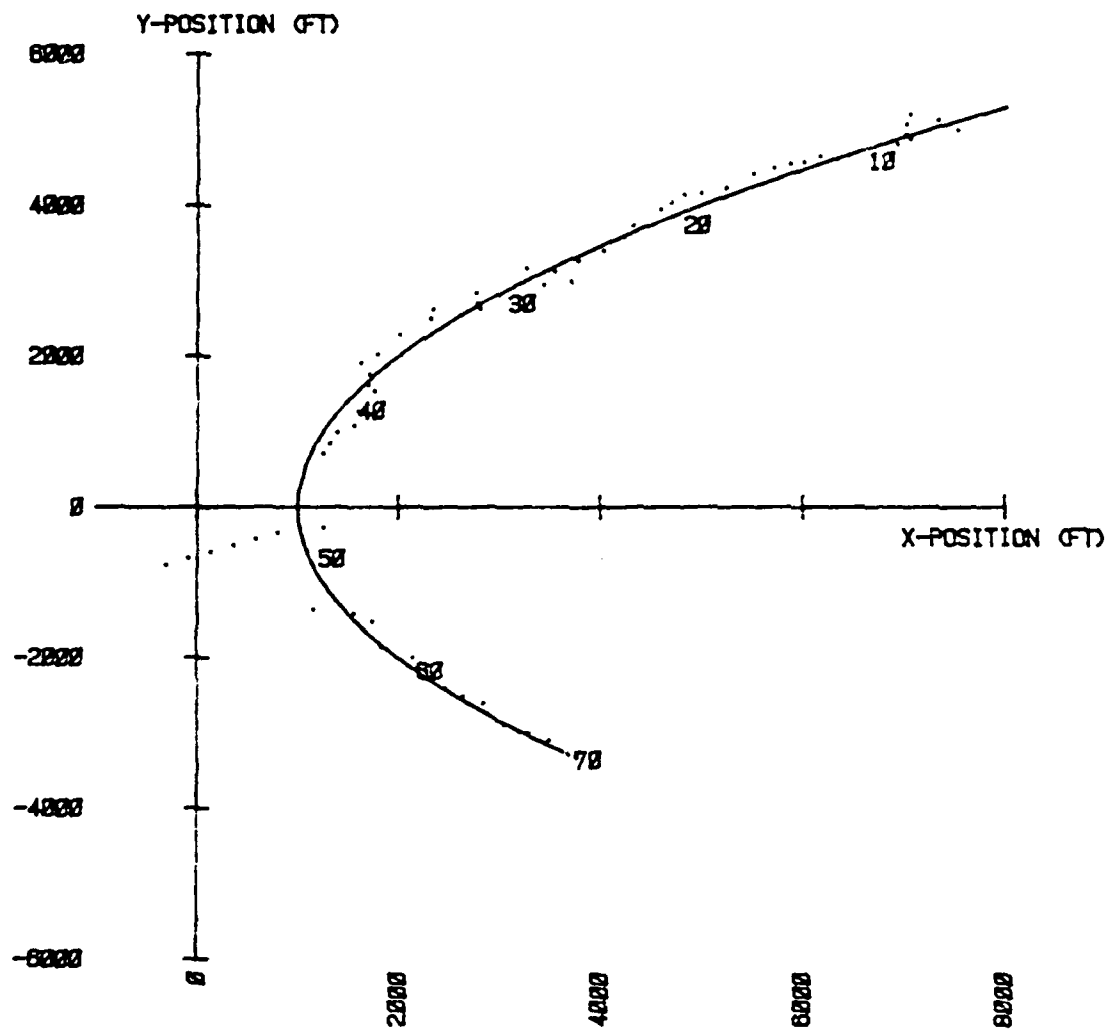
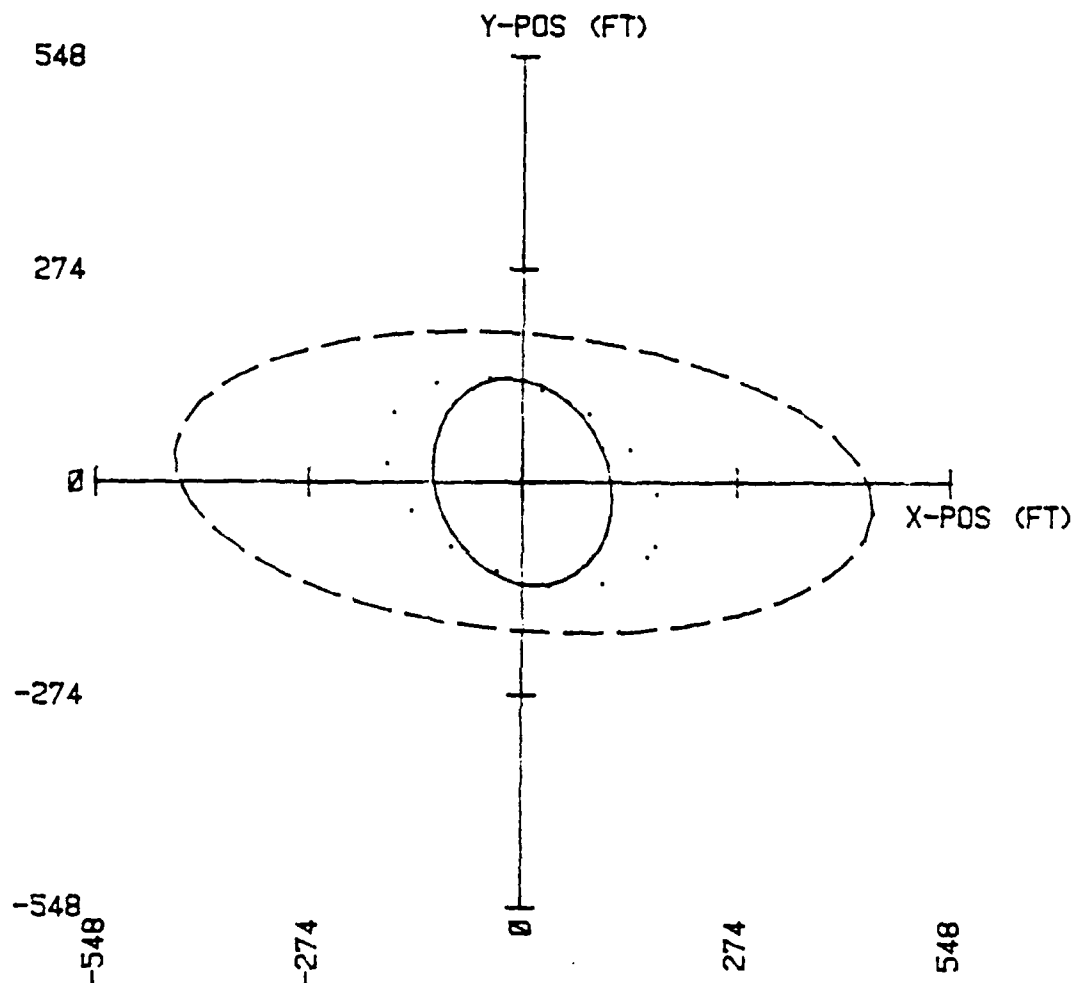


Figure 5.19 Filtered Track 3 for $\sigma_v=300$, $\sigma_w=10$, $R=20,000$,
Statistics Window 10, Reinitialized at 5
Consecutive Ellipse Area Increments



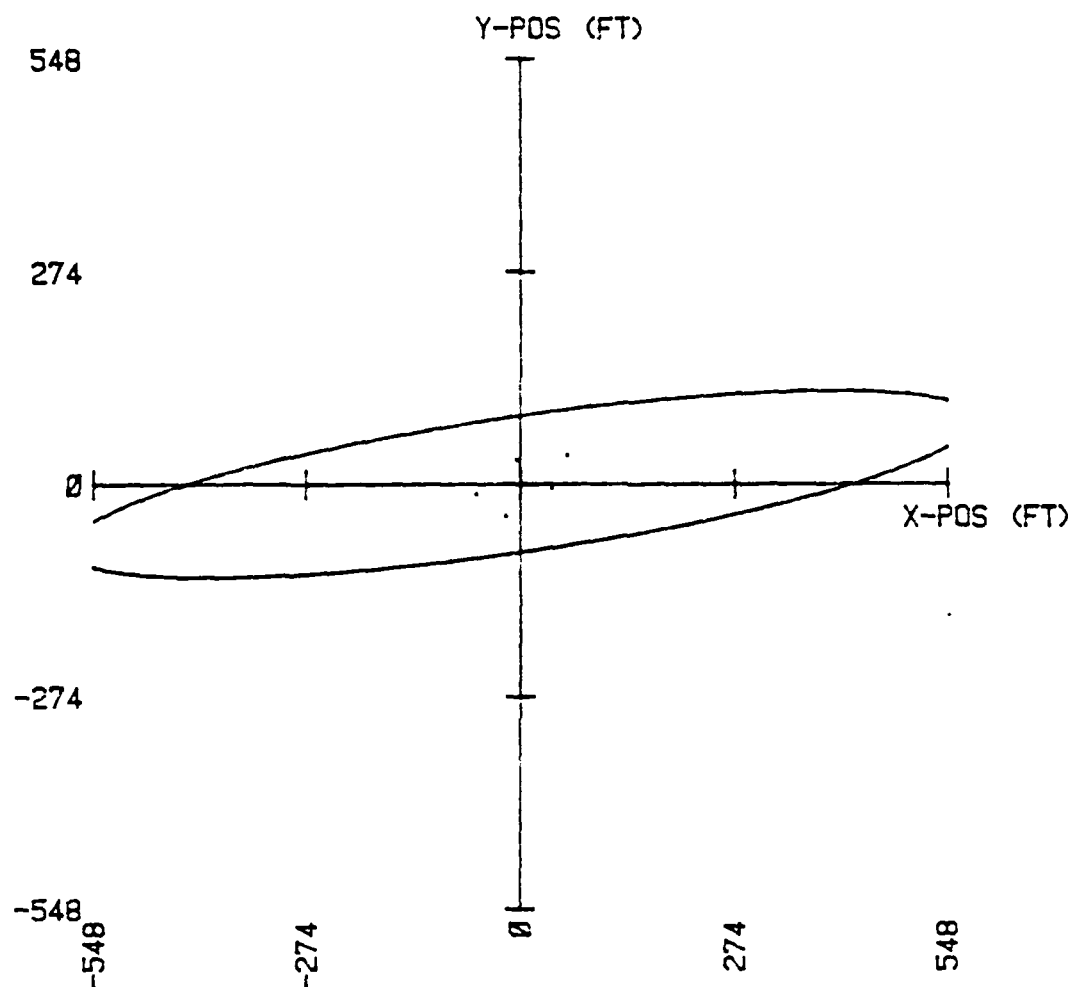
COVW=100 SIGV=300 R=20000 TIME AREA(SQ FT) LEG RESET

30 4734E+001 ——— 29

40 7035E+001 35

50 2698E+002 - - - 44

Figure 5.20 Filtered Track 3 Error Ellipses, $\sigma_v=300$, Statistics Window 10, Reinitialize_v5



COVW=100 SIGV=300 R=20000 TIME AREA(SQ FT) LEG RESET

60 1617E+002 ---- 52

70 6563E+000 52

Figure 5.21 Filtered Track 3 Error Ellipses, $\sigma_y=300$,
Statistics Window 10, Reinitialized 5

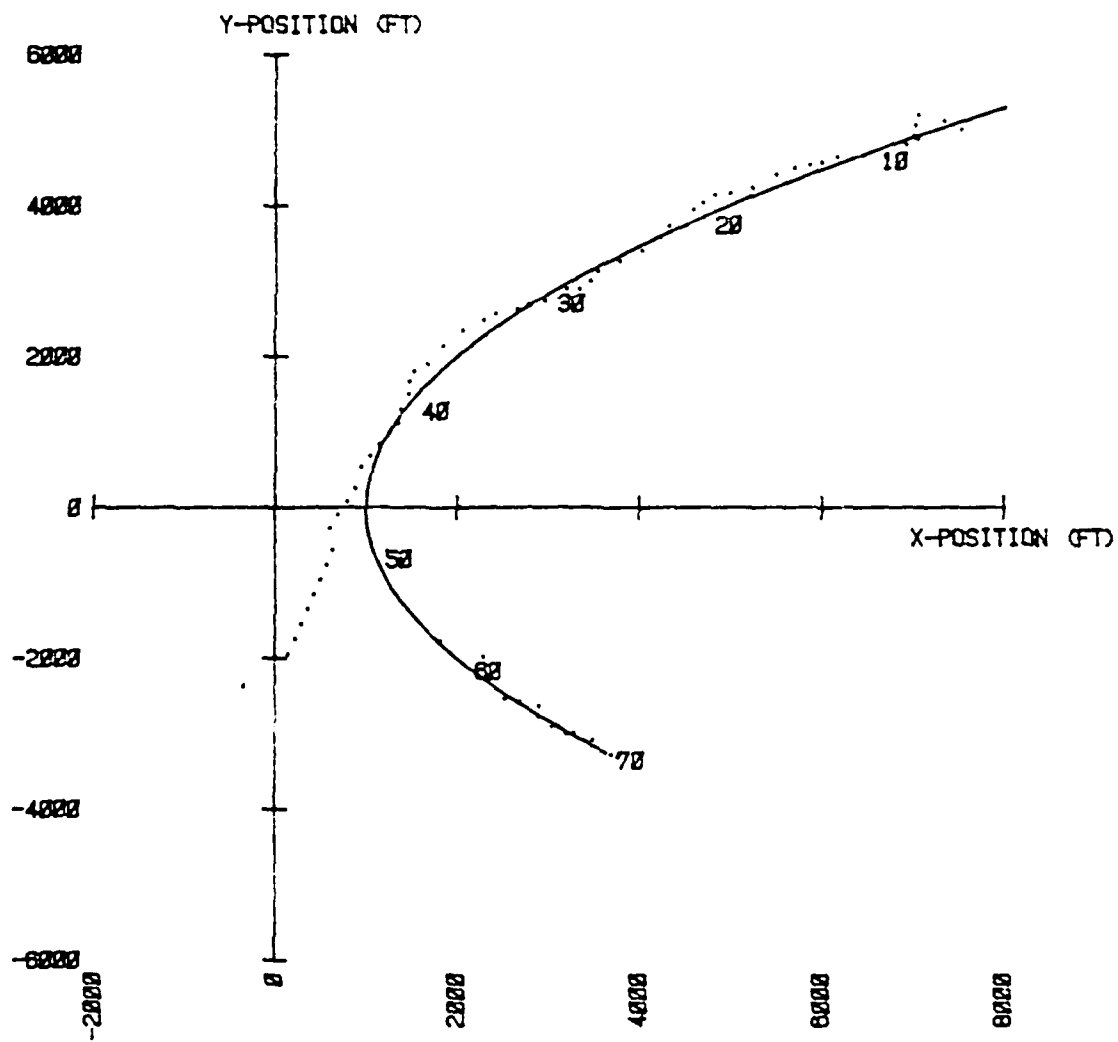
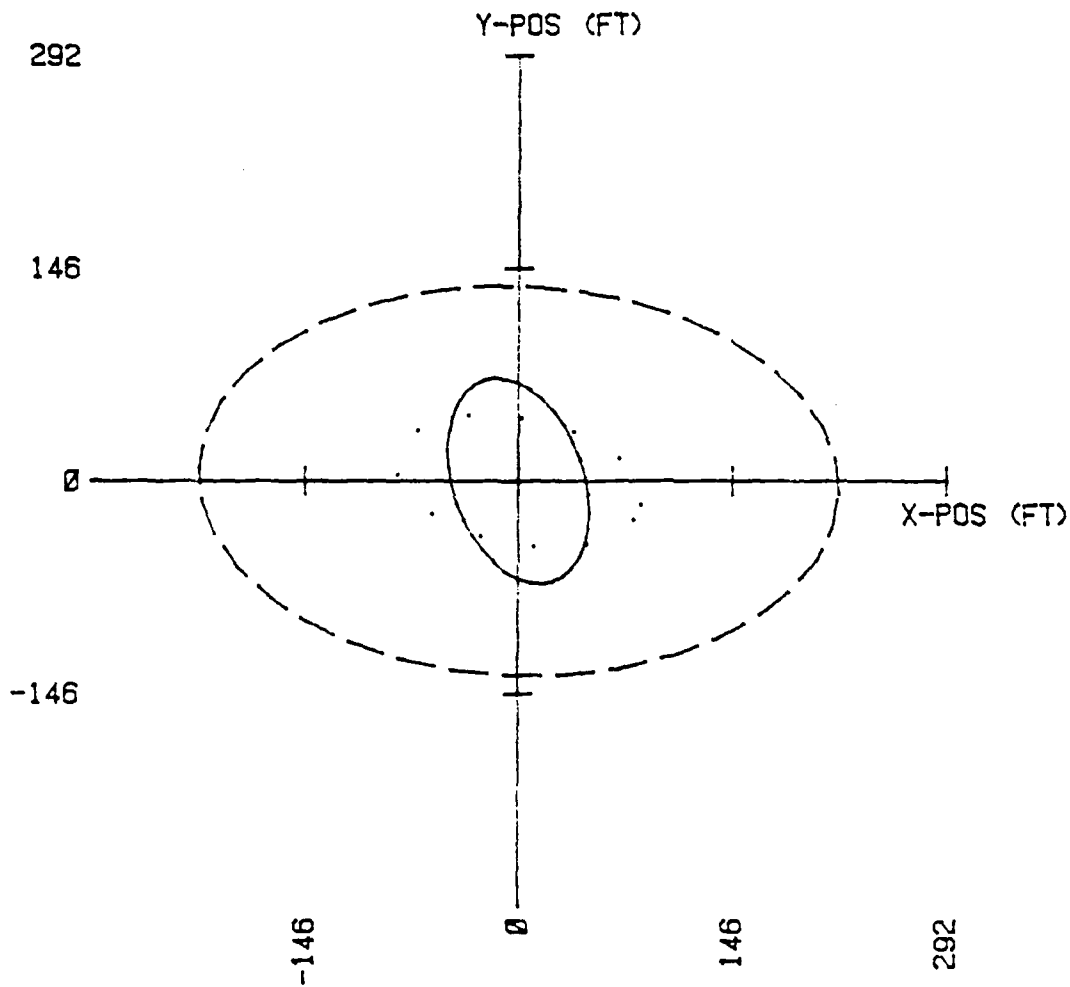
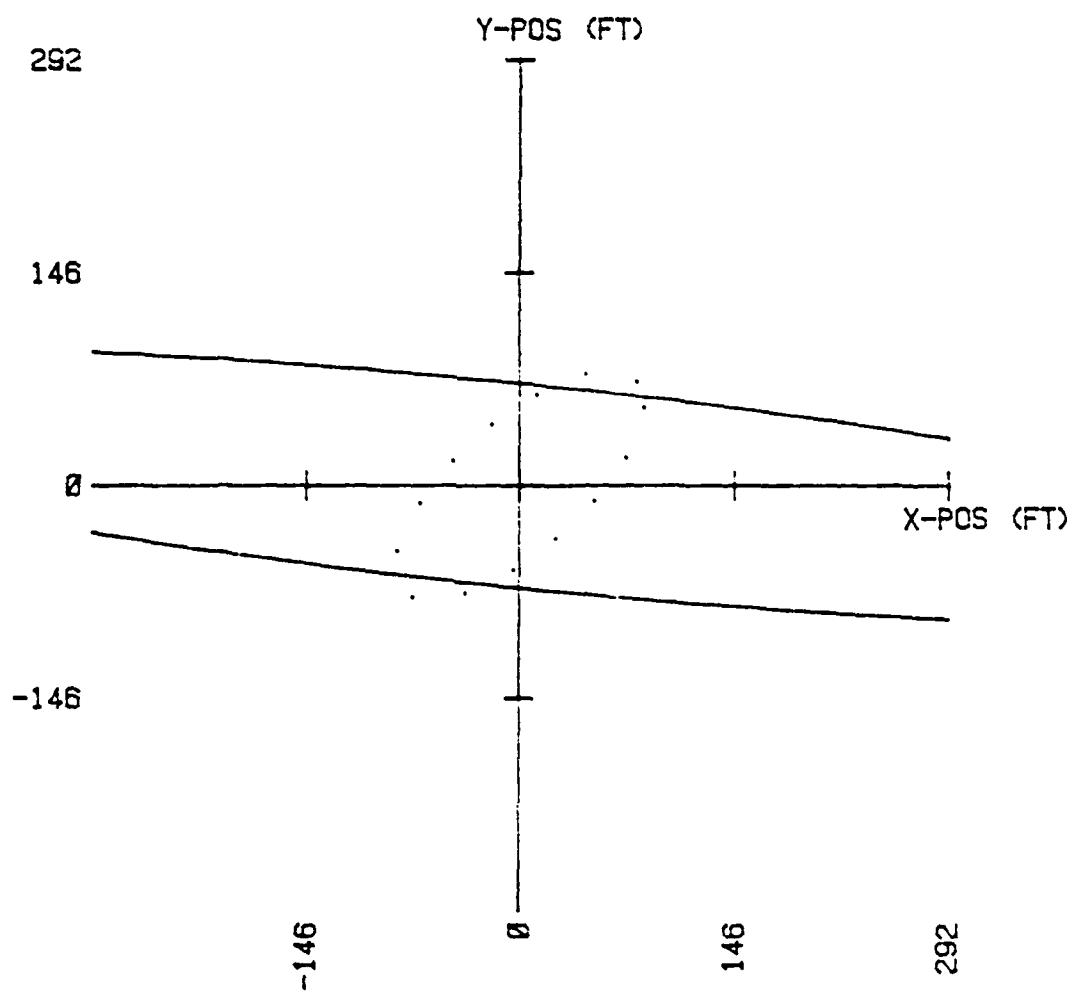


Figure 5.20 Filtered Track 3 for $\sigma_v=300$, $\sigma_w=10$, $R=20,000$
Statistics Window 10, Reinitialize 10



COVW=100	SIGY=300	R=20000	TIME	AREA (SQ FT)	LEG	RESET
			30	1024E+001	—	0
			40	1161E+001	0
			50	9186E+001	- - -	0

Figure 5.23 Filtered Track 3 Error Ellipses, $\sigma_y=300$,
Statistics Window 10, Reinitialize 10



COVW=100 SIGV=300 R=20000 TIME AREA(SQ FT) LEG RESET
 60 1380E+002 ——— 57
 70 1478E+001 57

Figure 5.24 Filtered Track 3 Error Ellipses, $\sigma_v=300$,
 Statistics Window 10, Reinitialize 10

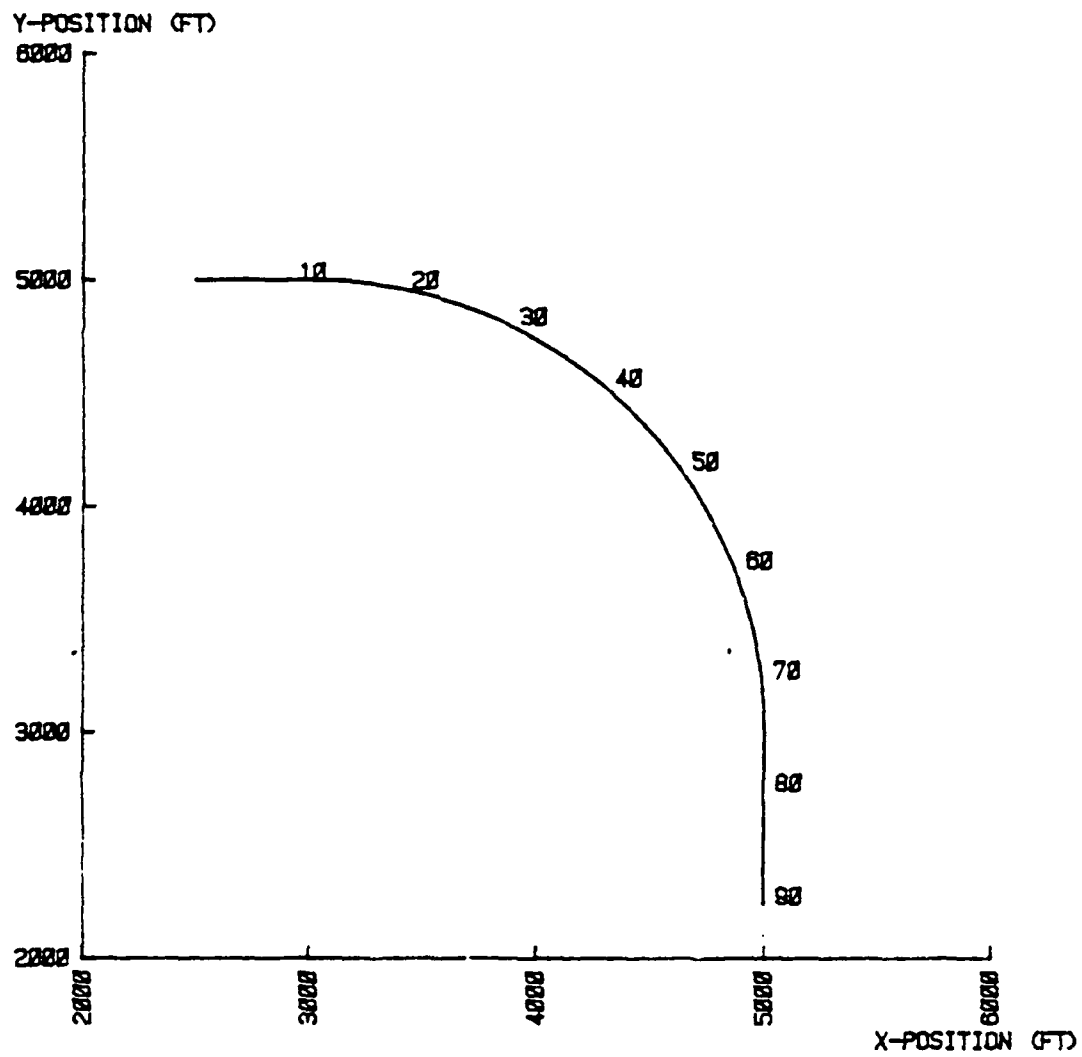


Figure 5.25 Track 4, Vel 50 ft/sec

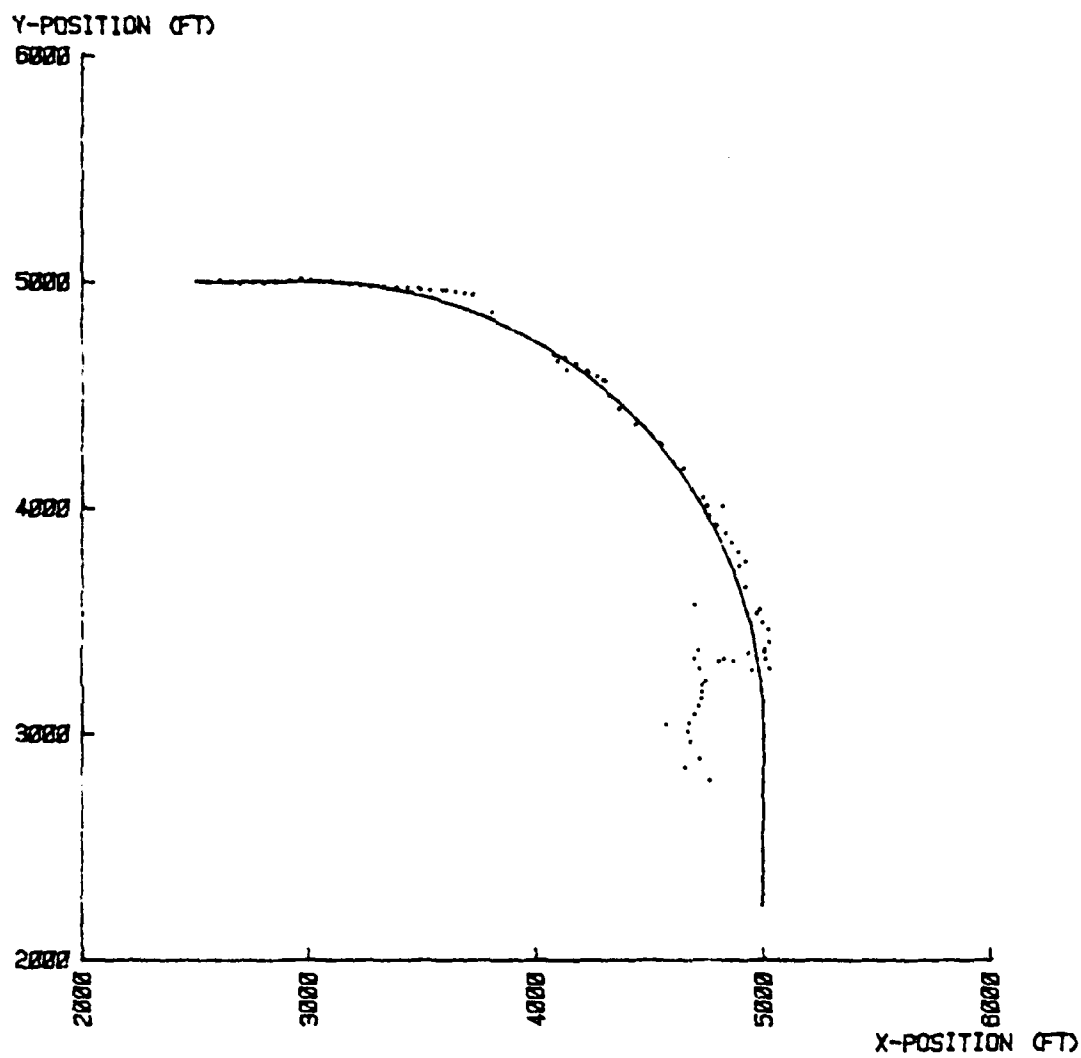


Figure 5.26 Filtered Track 4, $\sigma_v=30$, $R=900$, $\sigma_w^2=150$

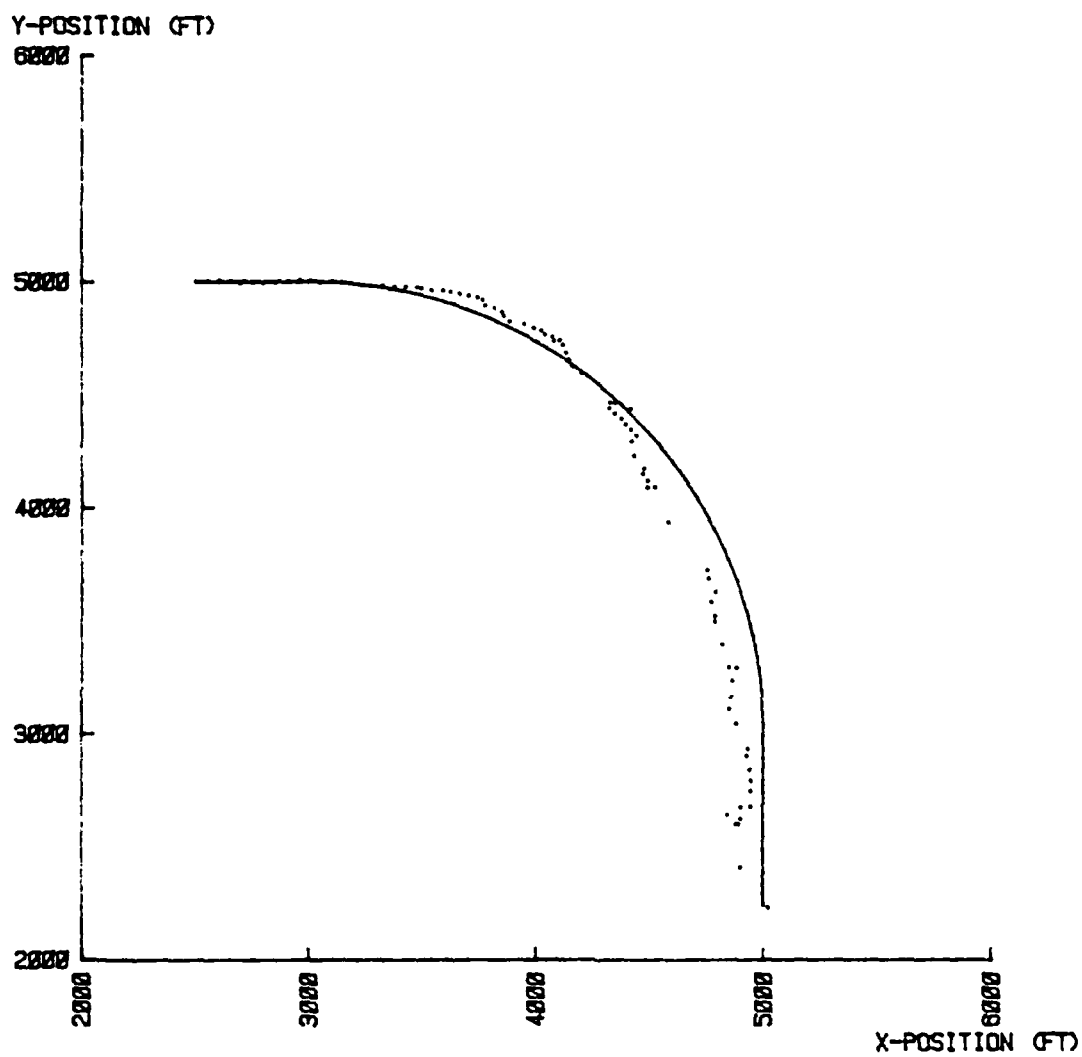
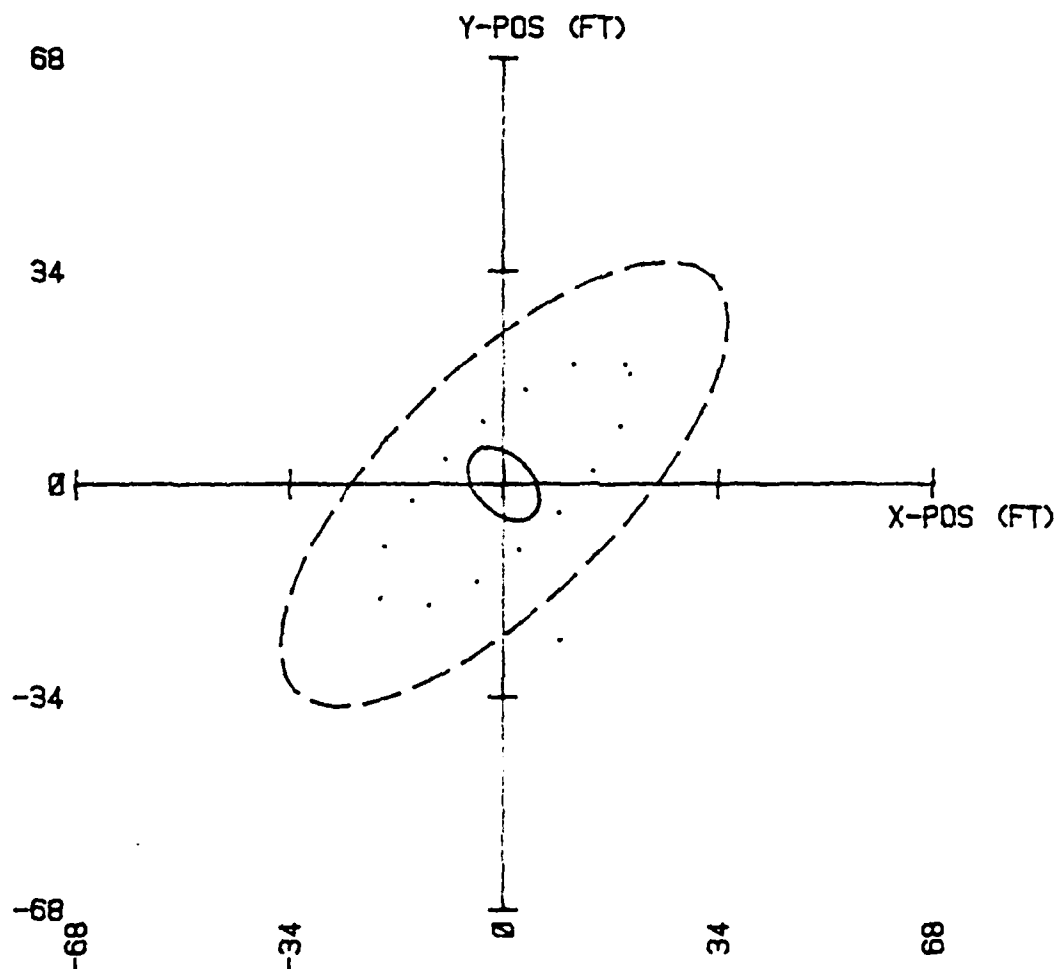
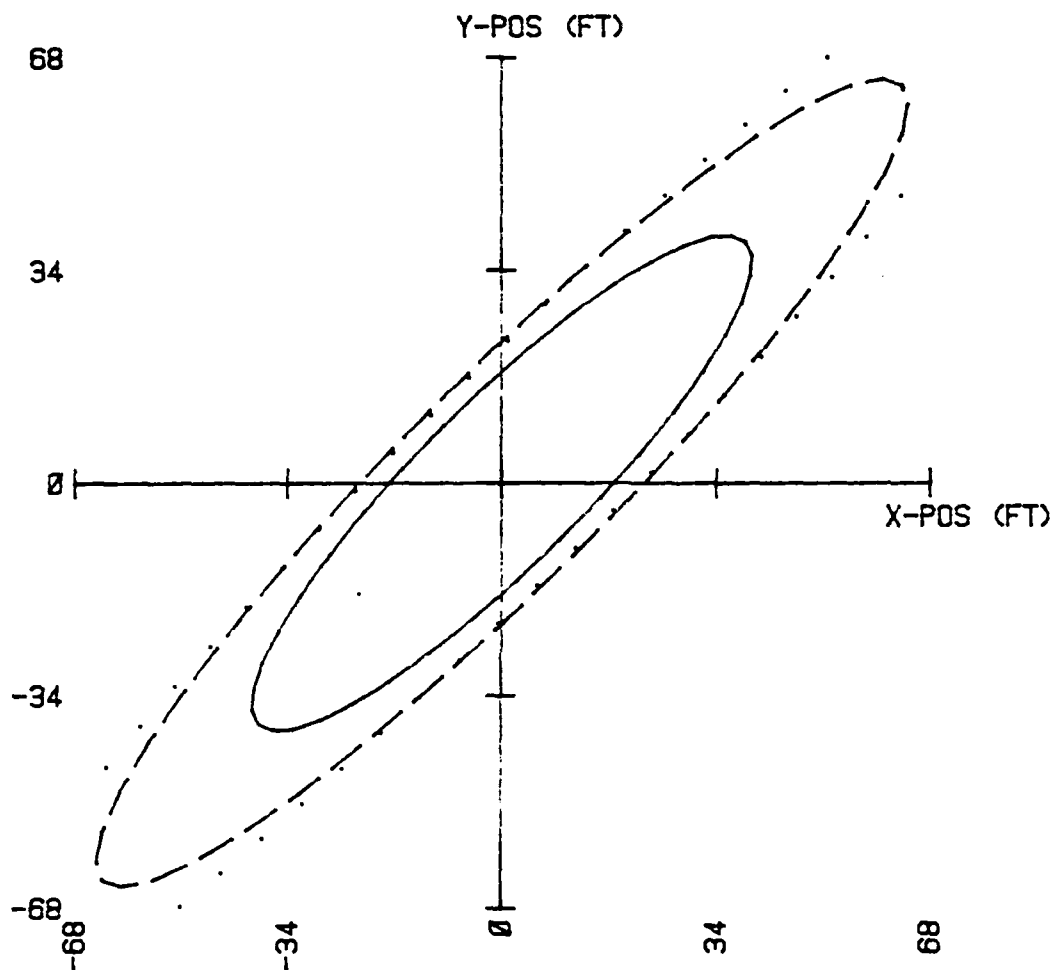


Figure 5.27 Filtered Track 4, $\sigma_v=30$, $R=900$, Statistics
Window 10, Varying σ_w^2



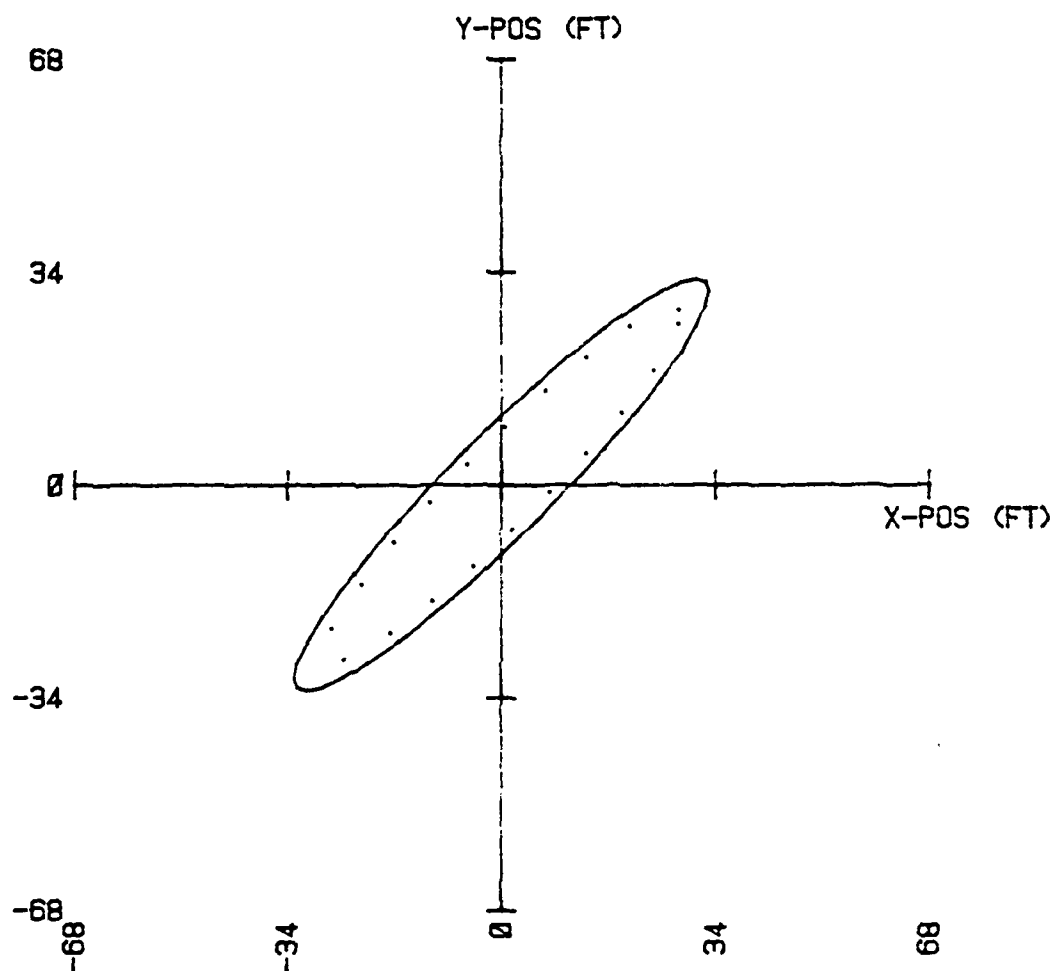
SIGV = 30	R = 900	TIME	AREA (SQ FT)	LEG.	COVW
		15	9688E-002	—	20
		25	8097E-001	40
		35	2740E+000	- - -	160

Figure 5.28 Filtered Track 4 Error Ellipses, Statistics Window 10, Varying COVW



SIGV = 30 R = 900		TIME	AREA (SQ FT)	LEG.	COVW
45	2239E+000	—	160		
55	6303E+000	160		
65	4625E+000	- - -	80		

Figure 5.29 Filtered Track 4 Error Ellipses, Statistics Window 10, Varying COVW



SIGV = 30	R = 900	TIME AREA (SQ FT)	LEG.	COVW
		75 1163E+000	—	40
		85 7916E-001	40

Figure 5.30 Filtered Track 4 Error Ellipses, Statistics
Window 10, Varying COVW

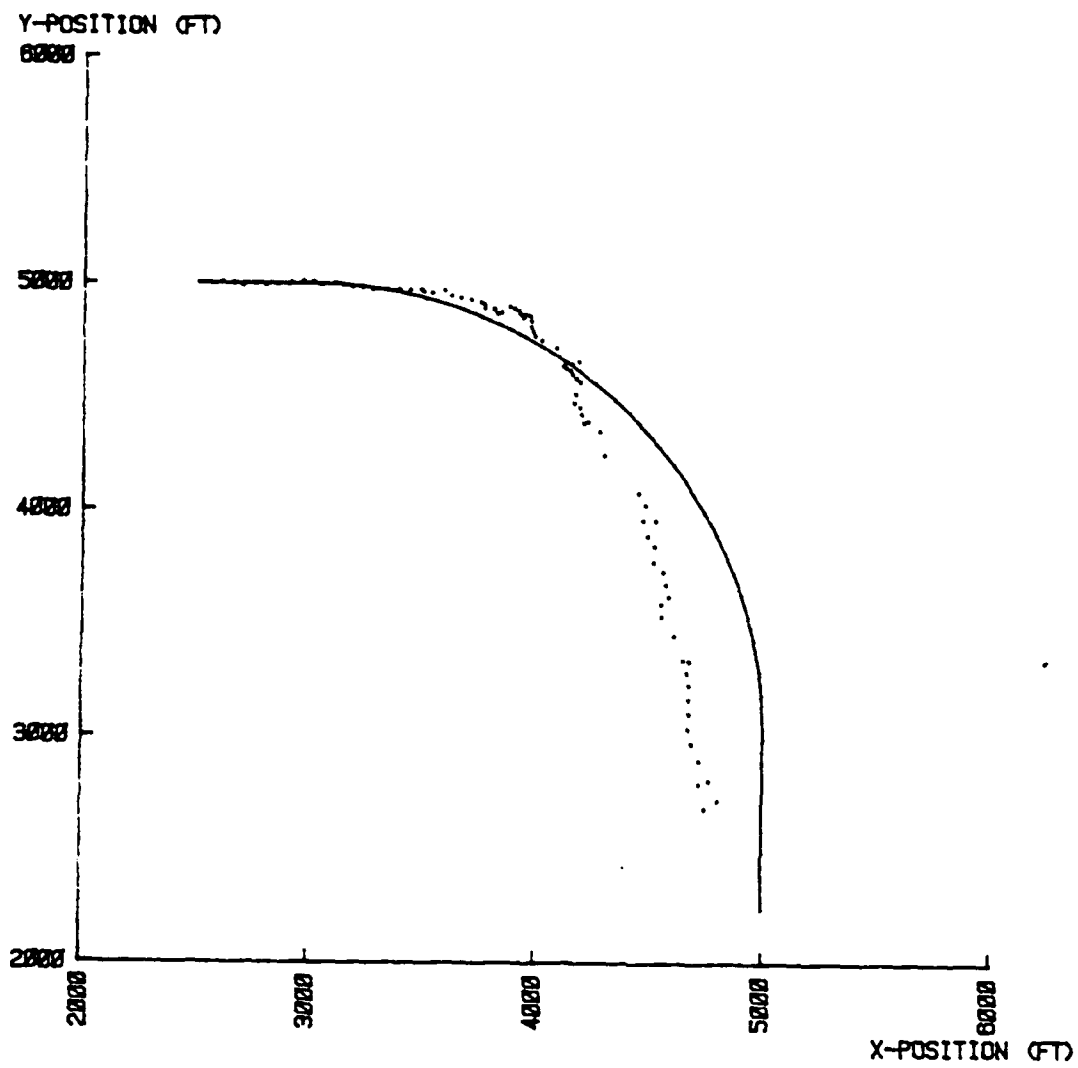
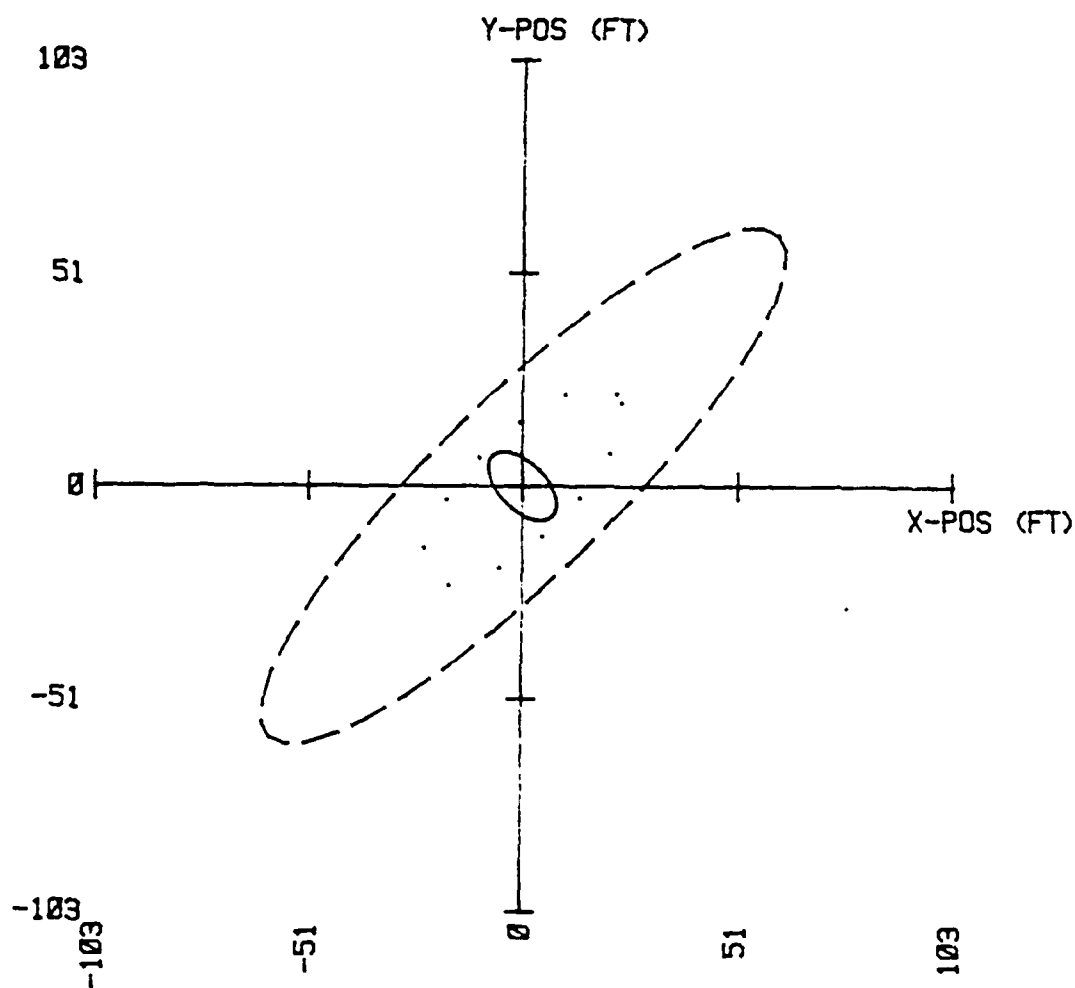


Figure 5.31 Filtered Track 4, $\sigma_v=30$, $R=900$, $\sigma_w^2=150$,
Reinitialize 5

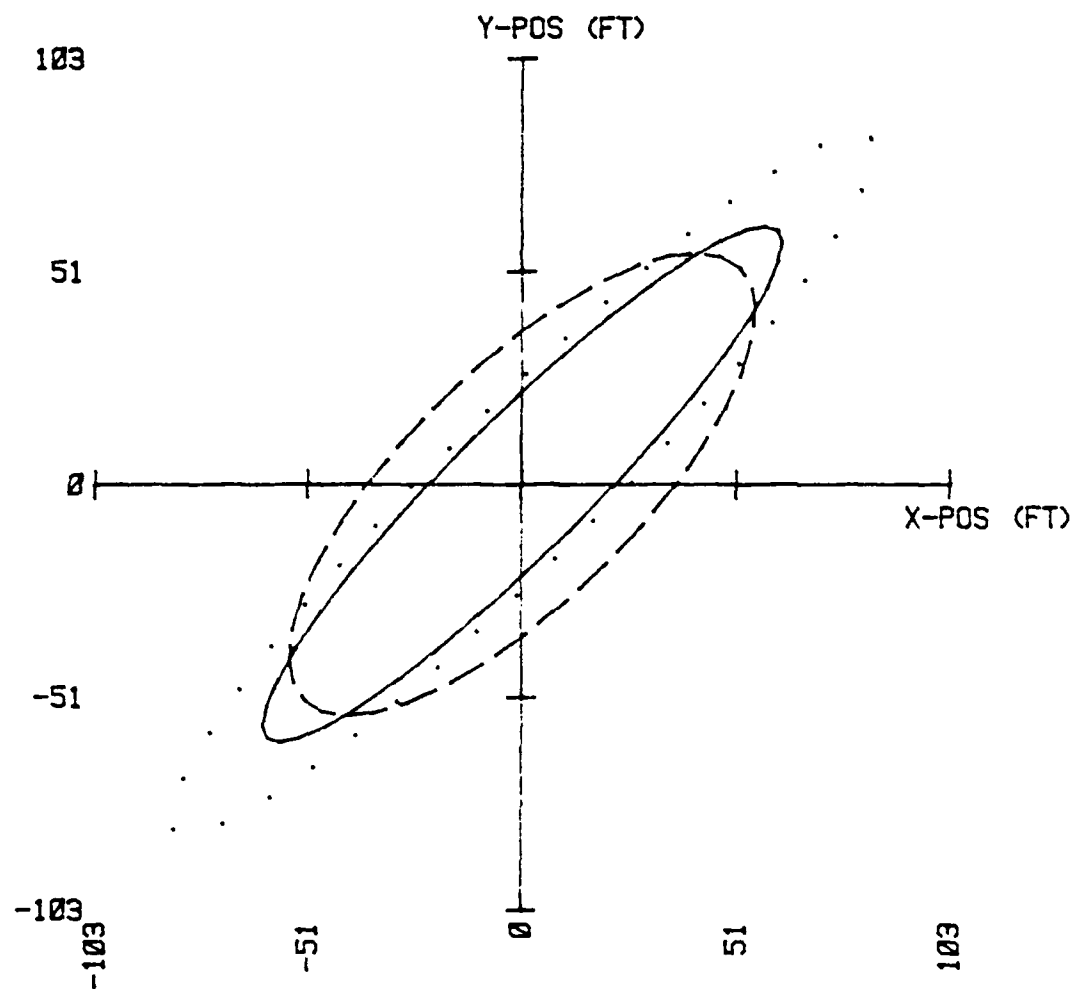


SIGV=30 R=900 COVW=150

TIME AREA (SQ FT) LEG. RESET

15	1805E-001	—	0
25	1211E+000	23
35	5743E+000	---	33

Figure 5.32 Filtered Track 4 Error Ellipses, $\sigma_v = 30$,
Reinitialize 5

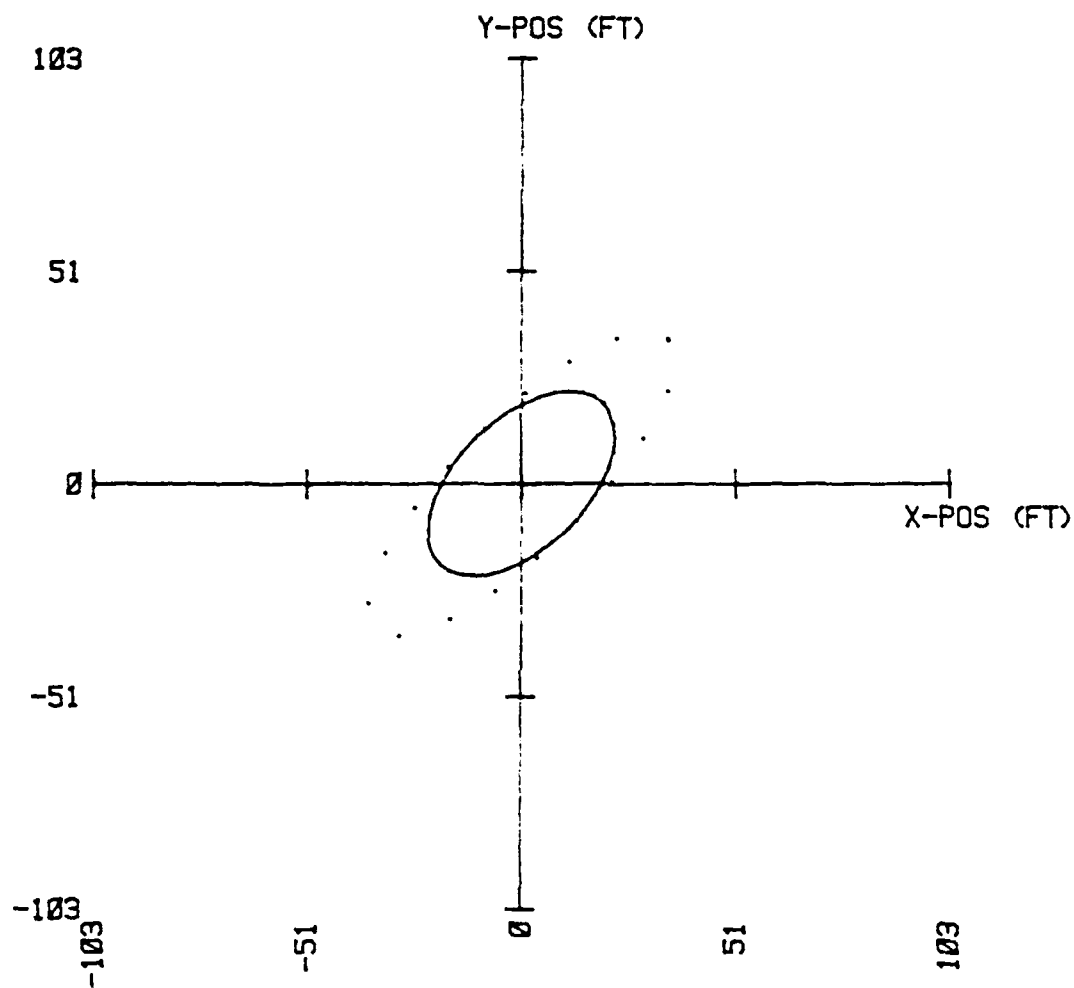


SIGV=30 R=900 COVW=150

TIME AREA(SQ FT) LEG. RESET

45	4383E+000	—	38
55	6852E+000	55
65	6495E+000	- - -	55

Figure 5.33 Filtered Track 4 Error Ellipses, $\sigma_y=30$,
Reinitialize 5



SIGV=30 R=900 COVW=150

TIME AREA(SQ FT) LEG. RESET

75	1348E+000	—	69
85	2452E+000	81

Figure 5.34 Filtered Track 4 Error Ellipses, $\sigma_v=30$,
Reinitialize 5

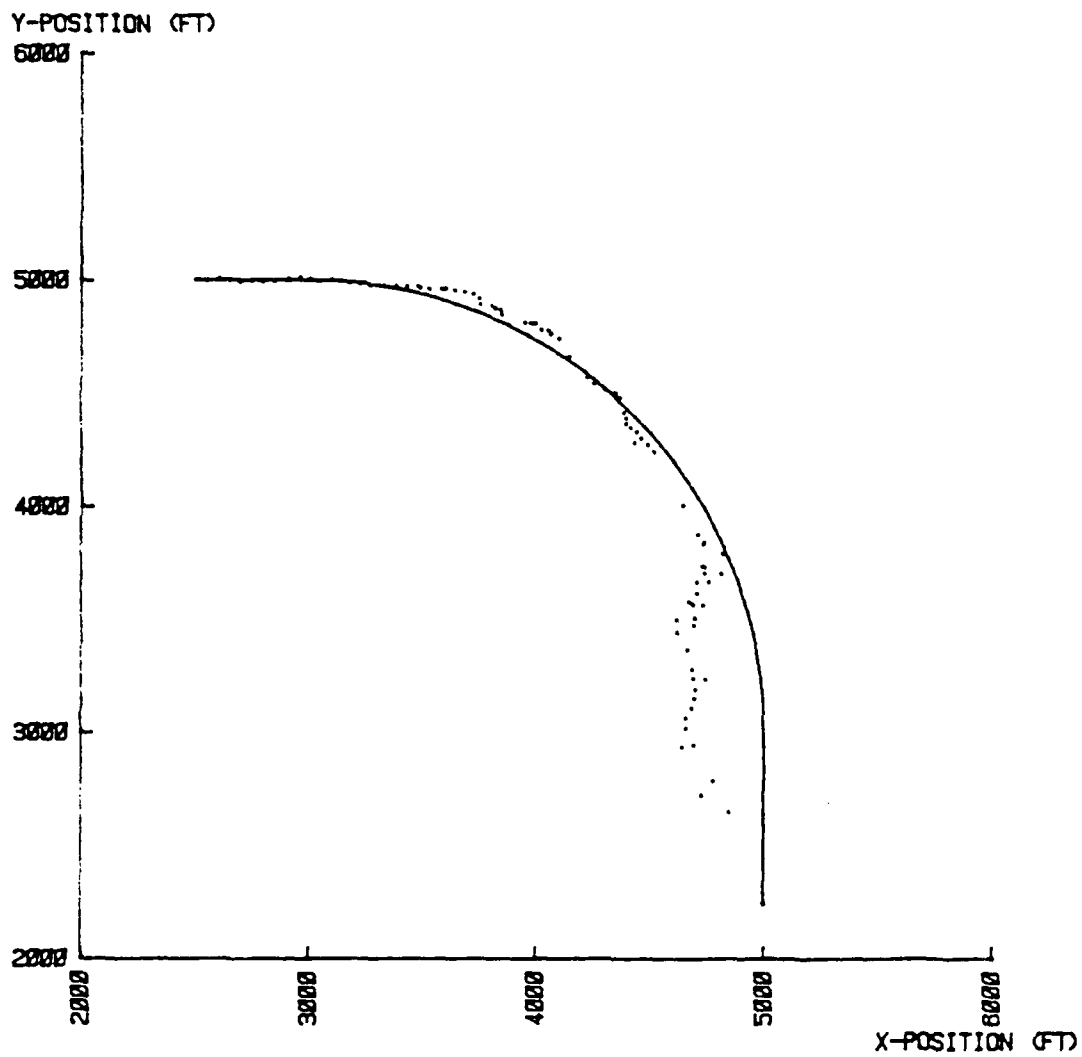


Figure 5.35 Filtered Track 4, $\sigma_v=30$, $R=900$, $\sigma_w^2=150$,
Reinitialize 7

VI. CONCLUSIONS AND RECOMMENDATIONS

A. ERROR ELLIPSE

The filter error ellipse proved useful as a tool for indicating filter performance. The information provided by the ellipse, particularly surface area changes, was used to make decisions concerning the alteration of the filter parameters. Several approaches for using the error ellipse were applied to both the linear and nonlinear tracking problem and the results are summarized below:

<u>Procedure</u>	<u>Applicable Filter (Linear or Extended)</u>	<u>Comments</u>
Statistics Window	Both	Useful in keeping the error ellipse current and responsive to present data. The ellipse reflects most recent data; old data is disregarded. Beneficial when making a decision concerning filter parameter modification. Normally a better indicator of filter convergence or divergence than without a statistics window.
Normalized Error Ellipse	Both	Aid in displaying error trends as target approaches coordinate axis or origin. Not practical in determining filter convergence/divergence due to rapid ellipse changes in vicinity of axes.

Reinitialize Filter-	Linear-Set $B(0)$	Use increasing ellipse size as an indicator of divergence, and as a decision-making device to reinitialize filter. Particularly valuable later in track when gains and $P(k+1/K)$ have settled out. More effective when used in conjunction with statistics window.
Increasing Ellipse Area	Extended-Set $P(k+1/K) = 10^N \times P_0$	
Error Ellipse Expansion/Compression to vary COVW (Adaptive Q)	Extended	This technique of varying COVW based on error ellipse area increase or decrease is particularly useful in a tracking environment containing large variations in the random forcing input. The procedure is more effective when used in conjunction with a statistics window. Using this technique with filter reinitialization was unsuccessful.

B. COMPUTER PERFORMANCE

The HP-86 proved to be an extremely reliable computer with no downtime experienced during the 5 month period of operation. Full(Real) precision was used throughout the study providing 15 digit precision, which was more than adequate. The use of the Matrix ROM reduced program length by 90% and increased computing speed by a factor of about 6. Although not used in this study, a Statistics ROM would have undoubtedly further increased computing speed. For any further study using the HP-86, it is recommended that a Statistics ROM be procured.

It took approximately 2 seconds for each incremental time measurement data to be sequenced through the filter equations, both for the linear and nonlinear case. This

computing time also included all statistics computations. With an incoming data rate of 1 set of measurement data per second, this computing speed is not sufficient for on-line processing. As previously mentioned, the Naval Underwater Tracking Range receives a series of 4 measurement times sequentially every 1.31 seconds. The range's three-dimensional tracking problem will necessarily involve more than the 4 state variables used in this study. Hence greater matrix dimensions resulting in longer computing times can be expected.

The HP-86 CRT graphics were used extensively to provide error ellipse plots during the tracking runs. Using a "no frills" approach to plotting, i.e. plotting without x-y axis or labelling, it took approximately 2.5 seconds per ellipse plot. The ellipse plotting routine used involved sines and cosines, plotted point by point in 30 degree increments for a total of 360 degrees. This method was somewhat slow. Had there been available a graphics program that would sketch in the ellipse around the intersected major and minor axis, the graphics presentation could have been speeded up. But since ellipse plotting for every 3 to 5 increments of time provided sufficient "real-time" information, the time of 2.5 seconds per plot was tolerable.

Summarizing, the HP-86 could be used to compute statistics and provide graphics in the real-time underwater tracking environment, if the graphics were required not more

often than 3 to 5 seconds. However, before the HP-86 can be considered feasible for real-time Kalman filter processing, more investigation is needed in finding ways to speed up computer processing time such as parallel processing, additional use of manufacturer-provided ROMs and machine language programming.

APPENDIX A
TRACK GENERATION

1. TRACK THREE

Target movement is in the x-y plane with the tracking sensor located at the origin of the cartesian axes. The target follows a parabolic track (see Figure A-1) at a constant speed of 200 feet per second.

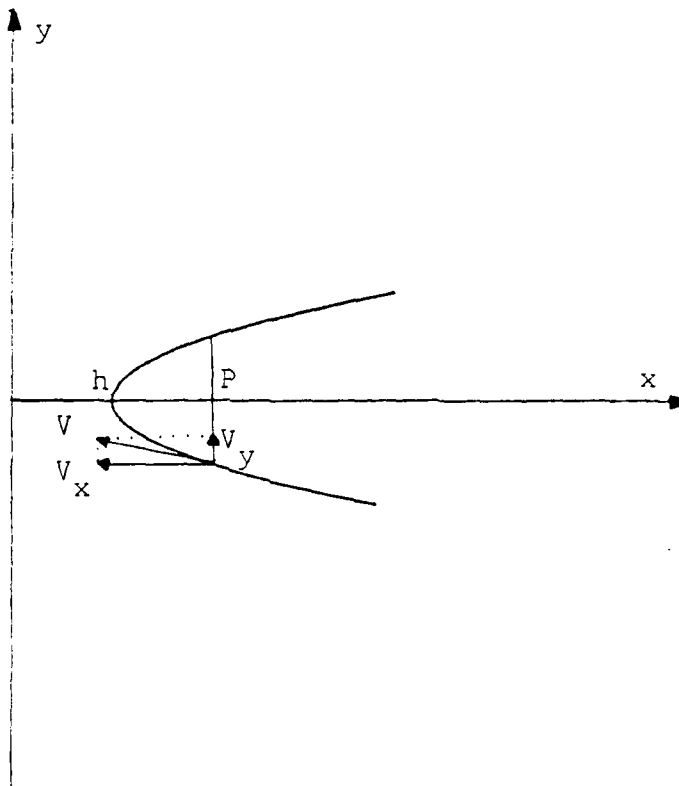


Figure A-1 Track 3

The parabolic equation is:

$$y^2 = 4p(x-h)$$

where $p = 1000$ and $h = 1000$, resulting in:

$$y^2 = 4000(x-1000)$$

Initial target location is $(x,y) = (8000, 5291.5)$. Target x-direction velocity is given by:

$$v_x = v \cos(\text{Angle}) \quad (\text{A-1})$$

and target y-direction velocity is:

$$v_y = v \sin(\text{Angle}) \quad (\text{A-2})$$

where the Angle is obtained from:

$$\text{Angle} = \tan^{-1}\left(\frac{\Delta y}{\Delta x}\right)$$

and v is obtained from:

$$v = (v_x^2 + v_y^2)^{1/2}$$

where the argument of the inverse tangent is the slope of a small increment (less than 1 second) at each successive data point. Using a sampling period of one second, the data points (x,y) can be obtained from:

$$x(k+1) = x(k) + v_x(k)$$

$$y(k+1) = y(k) + v_y(k)$$

Table A-1 gives the numerical values for the four states.

2. TRACK FOUR

Target movement simulates a 30-knot torpedo (velocity 50 feet per second) at a constant depth. The target's initial position is (x,y) = (3250, 5000), and it is moving in the v_x direction with $v_y=0$. (See Figure A-2.) The target remains on a straight course for 15 seconds, and then executes a 90 degree turn and travels in the -y direction at $v_y = -50$ ft/sec. The trajectory of the target turn is described by a 90 degree arc of a circle of radius, $R = 1000$, with the circle centered at (x,y) = (4000, 4000). The 90 deg arc will be traversed in:

$$2\pi R/4v \text{ sec.} = 10\pi \text{ sec. (where } v = 50 \text{ ft/sec)}$$

TABLE A-1
NUMERICAL VALUES OF STATES FOR TRACK THREE

K	X	X-VEL	Y	Y-VEL
1	8000.00	-186.90	5291.50	-71.15
2	7813.10	-186.93	5220.38	-71.13
3	7626.17	-186.60	5148.27	-71.98
4	7439.58	-186.25	5075.26	-72.87
5	7253.33	-185.89	5001.33	-73.79
6	7067.44	-185.51	4926.43	-74.74
7	6881.93	-185.11	4850.54	-75.73
8	6696.82	-184.68	4773.60	-76.76
9	6512.14	-184.24	4695.59	-77.83
10	6327.90	-183.76	4616.45	-78.94
11	6144.14	-183.26	4536.14	-80.09
12	5960.87	-182.73	4454.60	-81.30
13	5778.14	-182.17	4371.79	-82.56
14	5595.98	-181.57	4287.65	-83.87
15	5414.41	-180.92	4202.10	-85.24
16	5233.49	-180.24	4115.09	-86.68
17	5053.25	-179.51	4026.54	-88.19
18	4873.74	-178.72	3936.37	-89.78
19	4695.02	-177.87	3844.49	-91.44
20	4517.15	-176.96	3750.81	-93.19
21	4340.19	-175.97	3655.24	-95.04
22	4164.22	-174.91	3557.65	-97.00
23	3989.31	-173.74	3457.93	-99.06
24	3815.57	-172.48	3355.93	-101.25
25	3643.09	-171.09	3251.52	-103.57
26	3472.00	-169.57	3144.52	-106.05
27	3302.43	-167.89	3034.75	-108.68
28	3134.54	-166.04	2922.01	-111.50
29	2968.50	-163.98	2806.06	-114.51
30	2804.52	-161.67	2686.65	-117.74
31	2642.85	-159.09	2563.47	-121.21
32	2483.76	-156.17	2436.20	-124.94
33	2327.59	-152.86	2304.42	-128.98
34	2174.74	-149.07	2167.70	-133.33
35	2025.66	-144.72	2025.50	-138.05
36	1880.95	-139.67	1877.18	-143.15
37	1741.28	-133.78	1721.95	-148.67
38	1607.50	-126.83	1558.85	-154.64
39	1480.67	-118.59	1386.61	-161.05
40	1362.08	-108.70	1203.46	-167.88
41	1253.38	-96.73	1006.73	-175.05
42	1156.65	-82.01	791.58	-182.41
43	1074.64	-63.44	546.41	-189.67
44	1011.20	-37.24	211.63	-196.50
45	1000.00	0.00	0.00	-200.00

TABLE A-1 (CONT.)

K	X	X-VEL	Y	Y-VEL
46	1011.20	10.57	-211.63	-199.72
47	1021.77	25.14	-295.07	-198.41
48	1046.90	35.82	-433.13	-196.77
49	1082.72	48.89	-575.23	-193.93
50	1131.61	61.85	-725.57	-190.20
51	1193.46	74.49	-879.69	-185.61
52	1267.95	86.36	-1035.28	-180.39
53	1354.31	97.25	-1190.48	-174.77
54	1451.56	107.04	-1343.96	-168.94
55	1558.60	115.75	-1494.80	-163.10
56	1674.35	123.43	-1642.38	-157.37
57	1797.78	130.16	-1786.37	-151.35
58	1927.94	136.06	-1926.60	-146.58
59	2064.01	141.24	-2063.01	-141.61
60	2205.24	145.78	-2195.67	-136.92
61	2351.02	149.78	-2324.67	-132.54
62	2500.80	153.31	-2450.14	-128.43
63	2654.11	156.45	-2572.25	-124.60
64	2810.56	159.24	-2691.14	-121.01
65	2969.80	161.73	-2806.99	-117.66
66	3131.52	163.97	-2919.95	-114.52
67	3295.49	165.98	-3030.17	-111.58
68	3461.47	167.80	-3137.81	-108.82
69	3629.27	169.46	-3243.01	-106.23
70	3798.73	170.96	-3345.88	-103.79
71	3969.69	172.34	-3446.56	-101.49
72	4142.03	173.60	-3545.15	-99.32
73	4315.63	174.76	-3641.77	-97.26
74	4490.38	175.82	-3736.51	-95.32
75	4666.21	176.81	-3829.47	-93.48
76	4843.02	177.73	-3920.72	-91.73
77	5020.74	178.57	-4010.36	-90.06
78	5199.32	179.36	-4098.45	-88.48
79	5378.68	180.10	-4185.06	-86.97
80	5558.78	180.79	-4270.26	-85.53
81	5739.57	181.44	-4354.11	-84.15
82	5921.01	182.04	-4436.67	-82.83
83	6103.05	182.61	-4517.99	-81.57
84	6285.66	183.14	-4598.11	-80.36
85	6468.80	183.65	-4677.09	-79.20
86	6652.45	184.13	-4754.98	-78.09
87	6836.58	184.58	-4831.80	-77.01
88	7021.16	185.00	-4907.61	-75.98
89	7206.16	185.41	-4982.43	-74.99
90	7391.57	185.79	-5056.31	-74.03

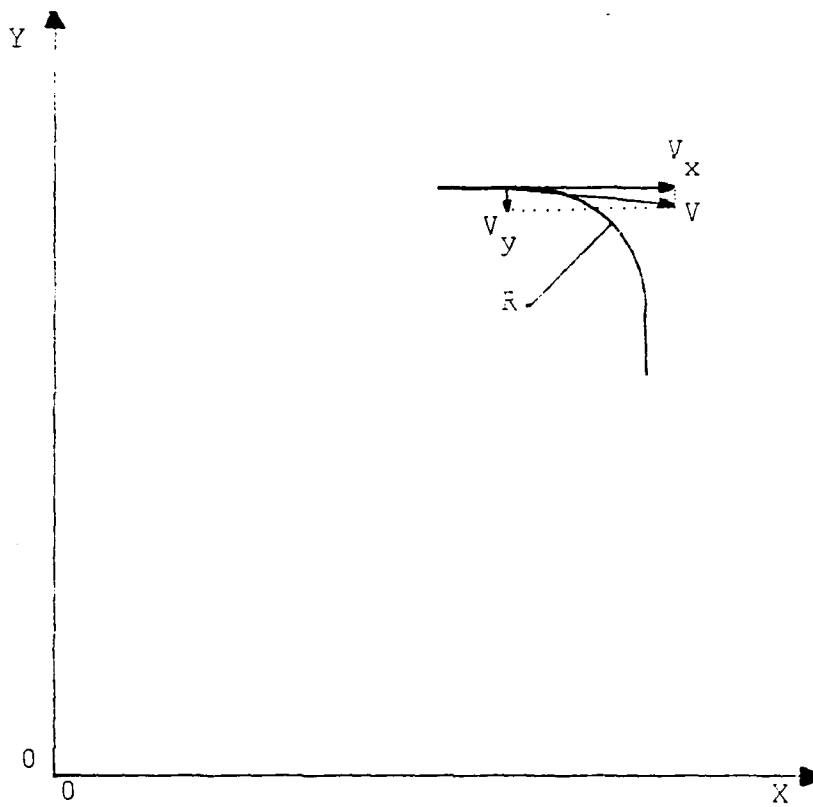


Figure A-2 Track 4

So each second:

$$\frac{2\pi/4}{10\pi} = .05 \text{ radians will be traversed}$$

Using the trigonometric identity:

$$\sin^2(A) + \cos^2(A) = 1$$

And the equation for a circle:

$$x^2 + y^2 = c^2$$

It follows that the arc of Figure A-2 is described by:

$$x(k) = 4000 + 1000\sin(.05k)$$

$$y(k) = 4000 + 1000\cos(.05k)$$

where the angle argument is in radians and $k=0,1,2,\dots,31$ seconds. The velocities v_x and v_y can be obtained from:

$$v_x(k) = 50\cos(.05k)$$

$$v_y(k) = -50\sin(.05k)$$

using the same angle argument.

The track values for the track arc are contained in Table A-2.

TABLE A-2

NUMERICAL VALUES OF STATES FOR TRACK FOUR

K	X	X-VEL	Y	Y-VEL
12	3049.99	49.98	4999.38	-1.25
13	3099.96	49.94	4997.50	-2.50
14	3149.86	49.86	4994.38	-3.75
15	3199.67	49.75	4990.01	-4.99
16	3249.35	49.61	4984.40	-6.23
17	3298.88	49.44	4977.54	-7.47
18	3348.22	49.24	4969.45	-8.71
19	3397.34	49.00	4960.13	-9.93
20	3446.21	48.74	4949.59	-11.16
21	3494.81	48.45	4937.82	-12.37
22	3543.09	48.12	4924.85	-13.58
23	3591.04	47.77	4910.67	-14.78
24	3638.62	47.38	4895.30	-15.97
25	3685.80	46.97	4878.75	-17.14
26	3732.55	46.53	4861.02	-18.31
27	3778.84	46.05	4842.12	-19.47
28	3824.64	45.55	4822.08	-20.62
29	3869.93	45.02	4800.89	-21.75
30	3914.68	44.46	4778.59	-22.87
31	3958.85	43.88	4755.17	-23.97
32	4002.43	43.27	4730.65	-25.06
33	4045.37	42.63	4705.05	-26.13
34	4087.67	41.96	4678.38	-27.19
35	4129.28	41.27	4650.67	-28.23
36	4170.19	40.55	4621.93	-29.25
37	4210.37	39.80	4592.17	-30.26
38	4249.79	39.04	4561.41	-31.24
39	4288.44	38.24	4529.68	-32.21
40	4326.27	37.42	4497.00	-33.16
41	4363.28	36.58	4463.38	-34.08
42	4399.43	35.72	4428.84	-34.99
43	4434.71	34.84	4393.41	-35.87
44	4469.10	33.93	4357.11	-36.73
45	4502.56	33.00	4319.97	-37.56
46	4535.09	32.05	4281.99	-38.38
47	4566.65	31.08	4243.22	-39.17

TABLE A-2 (CONT.)

K	X	X-VEL	Y	Y-VEL
48	4597.24	30.09	4203.67	-39.93
49	4626.83	29.08	4163.37	-40.67
50	4655.40	28.06	4122.34	-41.39
51	4682.54	27.02	4080.60	-42.07
52	4709.43	25.95	4038.20	-42.74
53	4734.85	24.88	3995.14	-43.37
54	4759.18	23.79	3951.46	-43.98
55	4782.41	22.68	3907.19	-44.56
56	4804.54	21.56	3862.35	-45.11
57	4825.53	20.42	3816.97	-45.64
58	4845.38	19.28	3771.09	-46.13
59	4864.08	18.12	3724.72	-46.60
60	4881.61	16.95	3677.89	-47.04
61	4897.97	15.77	3630.64	-47.45
62	4913.14	14.58	3583.00	-47.83
63	4927.12	13.37	3535.00	-48.18
64	4939.89	12.17	3486.66	-48.50
65	4951.45	10.95	3438.01	-48.79
66	4961.79	9.73	3389.10	-49.04
67	4970.90	8.50	3339.93	-49.27
68	4978.78	7.26	3290.56	-49.47
69	4985.43	6.03	3241.01	-49.64
70	4990.83	4.78	3191.30	-49.77
71	4994.99	3.54	3141.47	-49.87
72	4997.90	2.29	3091.56	-49.95
73	4999.57	1.04	3041.59	-49.99
74	4999.98	-.21	2991.59	-50.00

APPENDIX B
COMPUTER PROGRAM EXPLANATION

1. LINKAL

The LINKAL program computes the filter gains, $GAIN(4,2)$, for the 4-state system and stores the gains in "LINGAIN.STORAG". The theoretical covariance of error matrix, $PKA(4,4)$, is also computed and stored in "LINCOV.STORAG". Several different sets of gain and covariance values were computed and stored for various values of measurement noise, $RMAT(2,2)$, and random forcing noise, $COVW(2,2)$.

2. LINEST

The LINEST program retrieves the appropriate gain schedule from storage and computes the optimal estimate, $XHAT(4,1)$, and the optimal one-step prediction, $XHK1K(4,1)$. The following capabilities are contained in the LINEST program:

a. Gating Scheme

If the absolute difference (DIFF) between the one-step prediction, $XHK1K$ and the noisy track value, $ZMAT$, is greater than the three-sigma gate, then the $GAIN$ matrix is disregarded and $XHAT$ is set equal to $XHK1K$.

b. Track Noise

By setting $NOITRAK = 1$, the random number generator, RND , and the resulting simulated noise produced, $V1$ and $V2$,

are bypassed and the track values corrupted with noise, \hat{X} , are retrieved from data file "NOITRAK.STORAG". If NOITRAK=1, then the random number generator is "reseeded" for each program run, producing a different set of noise values resulting in a unique noise corrupted track for each run.

c. Statistics Window

When WINDOW is set to 0, the filter state statistics are computed after each Monte Carlo run. The error mean, variance and position covariance are computed. If WINDOW is set to an integer, I , such that $\max k > I > 0$, the statistics will be computed based on the data compiled during the last I iterations of the simulation. If, for example, WINDOW=10, the computation of statistics will be based on the data obtained during the last ten iterations of k , and all previous data is disregarded.

d. Error Normalization

By setting NORM = 1, the error (ERR), which is defined as the difference between the true track value (TRAK) and the estimate (\hat{X}), is normalized. For all other values of NORM the relative error is used in computing the statistics.

e. Reinitializing Gains

The program has the option of reinitializing the gains to $G(0)$. This can be done by setting HIGH to an integer I , such that $\max k > I > 0$. If the surface area of the ellipsoid

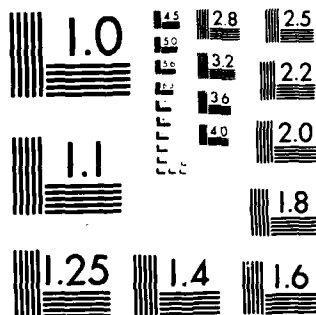
DEVELOPMENT OF REAL-TIME ERROR ELLIPSES AS AN INDICATOR
OF KALMAN FILTER PERFORMANCE(U) NAVAL POSTGRADUATE
SCHOOL MONTEREY CA J JAROS MAR 84

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[illegible]



MICROCOPY RESOLUTION TEST CHART
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increases I consecutive times, indicating filter divergence, the gains are reinitialized to $G(0)$. If reinitializing gains is not desired as an option, then HIGH is set to some arbitrary large number greater than max k.

3. EXTKF

The EXTKF program computes the optimal estimate, XHAT, and the optimal one-step prediction, XHK1K, for the 4-state nonlinear tracking problem. The EXTKF program has the options: gating scheme, track noise, statistics window, and error normalization as described for the LINEST program. EXTKF has the following additional options:

a. Reinitializing the Filter

The program has the option of reinitializing the covariance of one-step prediction error matrix, PK1K, by setting it to $10^n \times P_0$, where n is zero or some small integer. If HIGH is set to an integer I, such that $\max k > I > 0$, and the surface area of the ellipse increases I consecutive times, then the PK1K matrix will be reset to $10^n \times P_0$.

b. Adaptive Q

EXTKF has the option of automatically increasing or decreasing the state excitation matrix, Q, under certain conditions by changing the value of the covariance of excitation noise, COVW. INCREASE and DECREASE are set to integers I and J respectively, such that $\max k > I, J > 0$. If the surface area of the error ellipse increases I

consecutive times, COVW is doubled or increased by some factor. Conversely, if the surface area of the error ellipse decreases J consecutive times, COVW is halved or decreased by some factor. If COVW is changed, increased for example, the value of COVW can be changed again later in the run, if the criteria for either increasing or decreasing is met. If the adaptive Q is not desired then INCREASE and DECREASE are set to some large number greater than k.

APPENDIX C

PROGRAM LISTING

```

10 !linkal - this program computes the gain schedule and the
    error covariance matrix schedule for the linear kal. filter.
20 cpi=on base 1
30 real phi(4,4), cmat(2,4), gamma(4,2), covv(2,2), imat(2,2)
40 real pk1k(4,4), tempf1(4,2), gmat(2,4), gmat(4,4)
50 real tempf2(4,2), tempf3(4,2), gtemp5(4,4)
60 real gtemp6(4,4), pkk(4,4), temp7(4,4), temp8(4,4), cmat(4,2)
70 real tempf4(4,4), p1gain5 .storag
80 assign# 1 c "lincv5 .storag"
90 assign# 2 phi
100 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
110 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
120 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
130 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
140 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
150 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
160 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
170 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
180 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
190 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
200 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
210 data read 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1
220 !***** matrix transpose *****
230 mat cmat = trn (cmat)
240 mat phi = trn (phi)
250 mat gmat = trn (gamma)
260 mat imat = idn
270 mat temp1 = covv * gmat
280 mat gmat = gamma * temp1
290 !***** compute gain schedule, gain{} and covariance matrix, p(k/k)
300 ! compute equations (2-10), (2-11), and (2-12).
    for k=0:n-1
310   disr temp2 = pk1k * cmat
320   disr temp3 = cmat * temp2
330   disr temp4 = temp3 + imat
340   disr gtemp5 = inv (gtemp)
350   disr gtemp6 = cmat * gtemp5
360   disr temp7 = pk1k * temp6
370   disr gain = temp7
380   disr gain = temp7
390   disr gain = temp7
400   disr gain = temp7

```

```

10 !lipse
20 !this program computes the estimated track for the linear kal-
   man filter using gain schedule and covariance matrix computed
   off-line. it also computes statistics and covariance of
   error matrix.
30 ! error matrix.
40 ! error base
50 ! option base
60 real gain(4,2),cmat(2,4),phi(4,4),xhkk(4,1),temp1(2,1),errsq(4)
70 real pkk(4,1),zmat(2,1),temp2(2,1),temp3(4,1),ekk(3)
80 real xhat(4,1),diff(2),err(4),ssum(4),mean(4),sumsq(4),var(4)
90 real covmat(4,4),seansq(4),meanseq(4),mnpord(4,4),tprod(4,4)
100 real prod(4,4),wssum(4,90),wsumsq(4,90),wtprod(4,90)
110 real wprcd(90),werrsq(4,90),wmean(4,90),wmeansq(4,90)
120 real wmeanseq(4,90),wvar(4,90),wcovmat(3,90),wmnpord(90)
130 n = 1
140 s = 1
150 t = 3
160 noise = 300
170 r = 2000
180 sigm = 10
190 norm = 0
200 pltarea = c
210 pl = 1
220 statflt = 0
230 noitrak = 1
240 high = 10
250 windcw = 10
260 first = 5
270 nr = 10
280 chg = 3
290 pt = chg + .5
300 scale = 0
310 s = 4
320 stp = 10
330 cl = 0
340 count = 0
350 larger = 0
360 reset = 0
370 flag = 0
380 zz = 0

! "1" if error is to normalized.
! "1" if only area is printed out, i.e. no ellipse.
! "1" if plotting on screen, otherwise on plotter.
! "1" if ellipse plotting from previously computed
   statistics.
! "1" if using previous noisy track from "noitrak".
! "1" indicate # of times ellipse increases consecu-
   tively before resetting gains.
! "0" if no statistics window, otherwise indicate
   the length of the window.
! indicate the first iteration of k to be plotted.
! plct the error ellipse every "nr" iterations of k
! clear the screen every "chg" plots.
! "1" if scale is to be changed after clearing.
! 1/e is the scale size of the ellipse.
! iterate the plct every "stp" degrees.

```



```

390 llarge = 0
400 assign# 1 tc "estdata .storag"
410 assign# 2 tc "datatrak7, drive0"
420 assign# 3 tc "lingain3 .storag"
430 assign# 4 tc "limest3 .storag"
440 assign# 5 tc "lincov3 .storag"
450 assign# 6 tc "statlin3 .storag"
460 assign# 7 tc "lincov3 .storag"
470 assign# 8 tc "noitrak7c .storag"
480 read# 1 : : fhi{k()}
490 read# 2 : : fhi{k()}
500 randcmize
510 deg
520 mat sumsq = zer
530 mat fprod = zer
540 for k = 1 to 70
550 if statplt=1 then 2080
560 read# 7 : : fhi{k()}
570 i*** compute 3-sigma gate *****
580 maxpk = fhi{k(1,1)}
590 for i = 2 to 70
600 if pk(i,i) > maxpk then maxpk = pk(i,i)
610 next i
620 gate = 3 * sqrt(maxpk + r)
630 if reset = 0 then 700
640 assign# 3 tc "lingain3 .storag"
650 assign# 7 tc "lincov3 .storag"
660 assign# 7 tc "lincov3 .storag"
670 reset = 0
680 l = k - 1
690 mat temp1 = cmat * fhi{k}
700 read# 2 : : fhi{k()}
710 if noitrak ***** compute track corrupted with noise *****
720 i*** ***** ***** ***** ***** ***** ***** ***** ***** ***** ***** *****
730 i*** ***** ***** ***** ***** ***** ***** ***** ***** ***** ***** *****
740 i*** ***** ***** ***** ***** ***** ***** ***** ***** ***** ***** *****
750 v1 = noise * 2 * (ind - .5)
760 v2 = noise * 2 * (ind - .5)
770 zmat {1,1} = fhi{k(1,1)} + v1
780 zmat {2,1} = fhi{k(2,1)} + v2
790
800

```

```

810      print# 8 : zmat()
820      goto 840
830      read# 8 : zmat()
840      !** compute the difference for the gate test *****
850      diff{1} = abs{xhklk{3,1} - zmat{1,1}}
860      diff{2} = abs{xhklk{3,1} - zmat{2,1}}
870      !** *****
880      !** compute xhat(k/k) *****
881      !** *****
890      read# 3 : gain()
900      if diff(i)>gate cr diff{2}>gate then mat xhat=xhklk @ goto 980
910      mat temp2 = zmat - temp1
920      mat temp3 = gain*temp2
930      mat xhat = xhklk + temp3
940      goto 980
950      !** ***** Print estimated track *****
960      !** disp "xhat("n:1:n")"
970      mat disp xhat,
980      print# 4 : xhat()
990      !** *****
1000      !** compute xhat(k+1/k) *****
1001      !** *****
1010      !** mat xhklk = phi*xhat *****
1020      !** compute statistics *****
1030      !** compute running sum of error *****
1031      !** *****
1040      mat err = trak - xhat
1050      if norm< 1 then 1100
1060      for i = 1 to 4
1070      if trak(i,1)=0 then trak(i,1)=1
1080      next i
1090      mat err = err/trak
1100      print# 5 : err()
1110      if window>0 then 1420
1120      mat ssum = err + ssum
1130      !** ***** compute the mean of the error *****
1140      zz = zz + 1
1150      mat mean = (1/zz)*ssum
1160      !** ***** compute the variance of the error *****
1170      mat errsq = err*err
1180      mat sumsq = errsq + sumsq
1190      mat mean2c = (1/zz)*sumsq

```

```

1200      mat meansq = mean.mean
1210      mat var = meansq - meansq
1220      ! ***** compute the running product mean *****
1230      for i = 2 to n
1240          for j = 1 to i-1
1250              tprod(i,j) = err(i)*err(j)
1260              tprod(i,j) = tprod(i,j) + prod(i,j)
1270              mnpred(i,j) = prod(i,j)/k
1280          next j
1290      next i
1300      ! ***** compute the diagonal terms of the cov of error matrix ***
1310      for i = 1 to n
1320          covmat(i,i) = var(i)
1330      next i
1340      ! ***** compute the cff-diagonal terms of the cov of error matrix**
1350      for i = 2 to n
1360          for j = 1 to i-1
1370              ccvmat(i,j) = mnpred(i,j) - mean(i)*mean(j)
1380              ccvmat(j,i) = covmat(i,j)
1390          next j
1400      next i
1410      goto 2090
1420      for i = 1 to 4
1430          weir(i,k) = err(i)
1440      next i
1450      if k = 1 then 1510
1460      if k > windcw then 1830
1470      for i = 1 to 4
1480          wssum(i,k) = weir(i,k) + wssum(i,k-1)
1490      next i
1500      goto 1540
1510      for i = 1 to 4
1520          wssum(i,k) = weir(i,k)
1530      next i
1540      ! ***** compute the mean of error *****
1550      for i = 1 to 4
1560          wmean(i,k) = 1/k*wssum(i,k)
1570      next i
1580      ! ***** compute the variance of error *****
1590      for i = 1 to 4
1600          weirsq(i,k) = weir(i,k)*weir(i,k)
1610      next i

```

```

1620 if k = 1 then 167C
1630 fcr i = 1 to 4
1640 wsumsq(i,k) = werrsq(i,k) + wsumsq(i,k-1)
1650 next i
1660 goto 1700
1670 fcr i = 1 to 4
1680 wsumsq(i,k) = werrsq(i,k)
1690 next i
1700 for i = 1 to 4
1710 wmeansq(i,k) = 1/k*wsumsq(i,k)
1720 wmean(k) = wmean(i,k)*wmean(i,k)
1730 wvar(i,k) = wmeansq(i,k) - wmean(k)*wmean(k)
1740 next i
1750 ***** compute the running mean product *****
1760 wtfprod(k) = werr(i,k)*werr(t,k)
1770 if k = 1 then 1800
1780 wtfprod(k) = wtfprod(k) + wtfprod(k-1)
1790 goto 1810
1800 wtfprod(k) = wtfprod(k)
1810 wtfprod(k) = 1/k*wtfprod(k)
1820 goto 2050
1830 ***** computing the window statistics *****
1840 fcr i = 1 to 4
1850 wssum(i,k) = werr(i,k) + wssum(i,k-1) - werr(i,k-window)
1860 next i
1870 ***** compute the mean of error *****
1880 fcr i = 1 to 4
1890 wmean(i,k) = 1/window*wssum(i,k)
1900 next i
1910 ***** compute the variance of error *****
1920 fcr i = 1 to 4
1930 werrsq(i,k) = werr(i,k)*werr(i,k)
1940 wsumsq(i,k) = werrsq(i,k) + wsumsq(i,k-1) - werrsq(i,k-window)
1950 next i
1960 fcr i = 1 to 4
1970 wmeansq(i,k) = 1/window*wsumsq(i,k)
1980 wmean(k) = wmean(i,k)*wmean(i,k)
1990 wvar(i,k) = wmeansq(i,k) - wmean(k)*wmean(k)
2000 next i
2010 ***** compute the running product mean *****
2020 wtfprod(k) = werr(i,k)*werr(t,k)
2030 wtfprod(k) = wtfprod(k) + wtfprod(k-1) - wtfprod(k-window)

```

```

2040 wnpprod(k) = 1/windcw*wnprod(k)
2050 covmat(s,s) = wvar(s,k)
2060 covmat(t,t) = wvar(t,k)
2070 covmat(s,t) = wnpfcd(k) - wmean(s,k)*wmean(t,k)
2080 if statpt=1 then read# 6 : ccvmat(s,s),covmat(t,t),covmat(s,t)a
2090 goto 2100
2100 print# 6 : covmat(s,s),covmat(t,t),ccvmat(s,t)
2110 covmax(k) = covmat(s,s)*ccvmat(t,t)
2120 if k<2 then 2210
2130 if covmax(k)>ccvmax(k-1) then larger = larger+1 else larger=0
2140 if larger<high then 2210
2150 reset = 1
2160 mat ssum = zer
2170 mat sumsq = zer
2180 mat fcd = zer
2190 zz = 0
2200 kreset = k
2210 ***** plot the error ellipse *****
2220 if k<first then 3110
2230 if k=first or (k-first) mod nr = 0 then 2240 else 3110
2240 ccunt = ccunt + 1
2250 ekk(1) = covmat(s,s)
2260 ekk(2) = covmat(t,t)
2270 ekk(3) = covmat(s,t)
2280 lx = ekk(1)
2290 ly = ekk(2)
2300 mmax = max {lx,ly} 3040
2310 mmin = min {lx,ly}
2320 if mmin <= 0 then 3040
2330 if mmax/mmin < 10000 then 2350
2340 if mmax = lx then llarge = 1 else llarge = 2
2350 if ekk(3) <> 0 then 2380
2360 theta = 0
2370 goto 2450
2380 if ekk(1) <> ekk(2) then 2410
2390 theta = 0
2400 goto 2450
2410 theta = .5*atn (2*ek(3)/(ek(1)-ek(2)))
2420 lx = {ek(1) + ek(2)}/2 + ek(3)/sin(2*theta)
2430 ly = {ek(1) + ek(2)}/2 - ek(3)/sin(2*theta)
2440 if lx<0 or ly<0 then 3110

```

```

2450 a = sqrt (lx)
2460 b = sqrt (ly)
2470 area = 3.1416*a*b
2480 if pl=1 then z=100
2490 if k=first then z=2520
2500 if count=1 and sscale = 1 then 2520
2510 goto 2550
2520 smax = max (a,b)
2530 pscale = e*smax
2540 nscale = -(e*smax)
2550 if pl=1 then flcflter is 1 else plotter is 805
2560 if cl<> 0 then 2600
2570 pt = chg + .5
2580 qclear
2590 if pl=0 then limit 28,241,35,184
2600 if pl=1 then locate 5,145,16,90 else locate 30,108,18,96
2610 scale nscale,pscale,nscale,pscale
2620 if cl<>0 then 1*nscale
2630 move pscale, iticn(ft)
2640 label "x-foi, iticn(ft)"
2650 move .2*nscale, 1.05*pscale
2660 label .2*nscale, iticn(ft)
2670 move .9*pscale, 1.05*pscale
2680 label .9*pscale, "time"
2690 move .4*nscale, area(sq ft)
2700 label .4*nscale, "area(sq ft)"
2710 move .3*nscale, 1.3*nscale
2720 label using 2710: "sigw=";sigw; sigv=";noise;" r=";r
2730 if sscale<>1 and k<>first then 2750
2740 if cl=0 then laxes pscale/2,pscale/2,0,0
2750 goto 2760
2760 if pl<> 1 and cl = 0 then laxes pscale/2,pscale/2,0,0
2770 if pl=1 then move .8*pscale,pt/(chg + 1)*pscale @ goto 2780
2780 move .9*pscale,pt/(chg + 1)*pscale
2790 if llarge = 0 then label using 2800: " " ;k;" " ;area;" y-axis"
2800 if llarge = 1 then label using 2800: " " ;k;" " ;area;" x-axis"
2810 else label using 2800: " " ;k;" " ;area;" y-axis"
2820 if llarge = 0
2830 if count = 1 then label using 2870: " " ;k;" " ;area;" ----"
2840 if count = 2 then label using 2870: " " ;k;" " ;area;" ...."
2850 if count = 3 then label using 2870: " " ;k;" " ;area;" -.-.-"

```

```

2860 if count = 4 then label using 2870: " "k:" "area:" ----"
2870 image 2a,dd,2a,4de,6a
2880 if flag = 0 then 2920
2890 move 1,7*nscale,pt/(chg+1)*pscale
2900 label "reset at k=";kreset
2910 flag = 0
2920 mcve 0,0 = 2 then line type 3
2930 if count = 3 then line type 5
2940 if count = 4 then line type 1
2950 fcr ang = 0 tc 360 step stp
2960 xx = cos(ang)*a
2970 yy = sin(ang)*b
2980 x1 = xx*cos(theta) - yy*sin(theta)
2990 y1 = yy*cos(theta) + xx*sin(theta)
3000 iplot x1,y1
3010 next ang
3020 goto 3050
3030 disp "k=";k;" no ellipse plotted. cut of scale."
3040 cl = cl + 1
3050 pt = pt - .4
3060 if cl = pt = chg then cl = 0
3070 if count = chg then count = 0
3080 goto 3110
3090 disp k
3100 next k
3110 assign# 1 to *
3120 assign# 2 to *
3130 assign# 3 to *
3140 assign# 4 to *
3150 assign# 5 to *
3160 assign# 6 to *
3170 assign# 7 to *
3180 assign# 8 to *
3190 assign#
3200 end

```

```

10 ! extkf - this program computes gain schedule, covariance matrix
11 ! and track estimates for 4 state tracking problem.
12 option base 1
13 deg
14 real hmat(4,4), hmat(4,4), pk(4,4), pk(4,4), rmat(1,1), trak(4,1)
15 real imat(4,4), xhmat(4,4), phi(4,4), phi(4,4), temp(4,4), temp2(1,1)
16 real TEMP3(1,1), temp3in(1,1), temp4(4,1), gain(4,1), temp5(4,4)
17 real temp6(4,4), zmat(1,1), chk(4,4), temp7(1,1), temp8(4,1)
18 real xhat(4,4), temp9(4,4), gama(4,2), gama(2,4)
19 real covw(2,2), tempq(2,4), qmat(4,4), ssum(4,4), mean(4)
20 real covsq(4,4), errsq(4,4), qmat(4,4), ek(3), meansq(4), var(4)
21 real sumsq(4,4), errsq(4,4), wprod(4,4), perr(3)
22 real meansq(4,4), wsumsq(4,4), wprod(4,4), wprod(4,4), wvar(4,70)
23 real wssum(4,70), wmean(4,70), wmeansq(4,70), wmeansq(4,70)
24 real wvar(4,70), wvar(4,70), wvar(4,70), wvar(4,70)
25 real wvar(4,70), wvar(4,70), wvar(4,70), wvar(4,70)
26 real reset(4,4)
27 randomize
28 assign# 1 tc "data"
29 ! area = 1
30 ! if only area is being computed, i.e. no
31 ! ellipse plotting.
32 ! "1" if plot on crt screen, otherwise on plotter.
33 ! "1" if plotting previously computed statistics.
34 ! number of states. ellipse.
35 ! x-state of error ellipse.
36 ! y-state of error ellipse.
37 ! "1" if pk error ellipse; otherwise statistics
38 ! ellipse.
39 ! "stat" is the iteration of k to begin keeping
40 ! statistics.
41 ! last k to be computed (>start and <91).
42 ! "1" if no statistics window, otherwise indicate
43 ! the length of the window. (plot must equal 0).
44 ! first iteration of k to be plotted (greater than
45 ! or equal to start).
46 ! clear the screen every "chg" plots.
47 ! "1" if scale is to be changed after clearing.
48 ! plot error ellipse every "nri" iterations of k.
49 ! "1" if error ellipse to be normalized.
50 ! "1" if using previously determined noisy track.
51 ! iterate plot every "stp" degrees.
52 ! standard deviation of noise.
53 covw(1,1) = 20

```



```

400 imat(1,1) = 900
410 increase = 9 ! # cf consecutive ellipse area increases before
    ! increasing q.
420 decrease = 5 ! # cf consec. ell area decreases before dec. q.
430 cl = 0
440 up = 0
450 down = 0
460 upflag = 0
470 downflag = 0
480 count = 0
490 out = 0
500 llarge = 0
510 matssum = zer
520 matsumsq = zer
530 matprod = zer
540 assign# 2 tc "set2set, drive0"
550 assign# 3 tc "perr8, storag"
560 assign# 4 tc "statmat8a, storag"
570 assign# 5 tc "errrex+8a, storag"
580 assign# 6 tc "xhaterx8a, storag"
590 assign# 7 tc "noitrak8, storag"
600 imat reset = idn
610 mat reset = (100)*imat
620 mat rk1k = reset
630 read# 1 : xhkrk()
640 read# 2 : fhi()
650 mat fhit = trn(fhi)
660 read# 2 : gama
670 mat gama t = trn(gama)
680 hmat{1,2} = 0
690 hmat{1,4} = 0
700 covw{1,2} = 0
710 covw{2,1} = 0
720 for k=1 to high
730 ! ***** reinitialize if conditions are met *****
740 if upflag=1 then covw(1,1)=2*covw(1,1) a upflag=0
750 if downflag=1 then ccw(1,1)=.5*covw(1,1) a downflag=0
760 ccw(2,2)=covw(1,1)
770 if statfpt = 1 then 2480
780 mat tempq = covw*camat
790 mat qmat = gama*tempq
800 read# 1 : trak()

```

```

810 if not trak = 1 then read# 7 : zmat() @ goto 850
820 v(1) = ncise*2*(ind - 5)
830 zmat(1,1) = sqrt(trak(1,1)**2 + trak(3,1)**2) + v(1)
840 print# 7 : zmat()
850 !*****conduct 3-sigma gate test *****
860 maxpk = pk1k(1,1)
870 fcr i = 2 to
880   if i = pk1k(i,i) > maxpk then maxpk = pk1k(i,i)
890   next i
900 gate = 3*sqrt(maxpk + imat(1,1))
910 hattrak = sqrt(xhkk1k(1,1)**2 + xhkk1k(3,1)**2)
920 diff = abs(hattrak - zmat(1,1))
930 if diff < gate then
940   mat pkk = pk1k
950   mat xhat = xhkk1k
960   print# 6 : xhat()
970   goto 1210
980   i = k-1
990   hmat(1,1) = xhkk1k(1,1)/sqrt(xhkk1k(1,1)**2 + xhkk1k(3,1)**2)
1000   hmat(1,3) = xhkk1k(3,1)/sqrt(xhkk1k(1,1)**2 + xhkk1k(3,1)**2)
1010   mat hmat = tin(hmat)
1020   mat temp1 = pk1k*hmat
1030   mat temp2 = hmat*temp1
1040   mat temp3 = temp2 + imat
1050   mat temp3in = (1)/temp3
1060   mat temp4 = hmat*temp3in
1070   mat gain = pk1k*temp4
1080   !*****compute the covariance matrix p(k/k) *****
1090   mat temp5 = gain*imat
1100   mat temp6 = imat - temp5
1110   mat pkk = temp6*pk1k
1120   !*****compute the estimate xhat(k/k) *****
1130   chk1k(1,1) = sqrt(xhkk1k(1,1)**2 + xhkk1k(3,1)**2)
1140   mat temp7 = zmat - chk1k
1150   mat temp8 = gain*temp7
1160   mat xhat = xhkk1k + temp8
1170   print# 6 : xhat()
1180   !*****compute xhat(k+1/k) *****
1190   xhkk1k(1,1) = xhat(1,1) + xhat(2,1)
1200   xhkk1k(2,1) = xhat(2,1)
1210   xhkk1k(3,1) = xhat(3,1) + xhat(4,1)
1220   xhkk1k(4,1) = xhat(4,1)
1230
1240
1250

```

```

1270C **** compute p(k+1/k) *****
1280 mat temp9 = pkk*phit
1290 mat temp9a = phi*temp9
1300 mat pk1k = temp9a + gmat
1310 if k<start then gcto 33370
1320 ferr{1} = pkk(s,s)
1330 ferr{2} = pkk(t,t)
1340 ferr{3} = pkk(s,t)
1350 print# 3: perr(i)
1360C **** compute statistics *****
1370C **** trak - xhat
1380C **** trak > 0 then 1760
1390C **** if norm<> 1 then 1470
1400C **** for i = 1 to 4
1410C **** if trak(i,1) = 0 then trak(i,1) = 1
1420C **** next i
1430C **** err/trak
1440C **** mat ssum = err + ssum
1450C **** print# 5: err(i)
1460C **** compute the mean of the error *****
1470C **** mat mean = (1/k)*ssum
1480C **** compute the variance of the error *****
1490C **** mat arisq = err*err + ssumsq
1500C **** mat sumsq = errsq + ssumsq
1510C **** mat meansq = (1/k)*sumsq
1520C **** mat meanksq = mean.meanksq
1530C **** mat var = meansq - meanksq
1540C **** compute the running product mean *****
1550C **** for i = 2 to n
1560C **** for j = 1 to i-1
1570C **** {prod(i,j) = err(i)*err(j)
1580C **** {prod(i,j) = tprod(i,j) + prod(i,j)
1590C **** {nprod(i,j) = prod(i,j)/k
1600C **** next j
1610C **** next i
1620C **** compute the diagonal terms of the cov of error matrix**
1630C **** for i = 1 to n
1640C **** covmat(i,i) = var(i)
1650C **** next i
1660C **** compute the off-diagonal terms of cov of error matrix ***
1670C **** for i = 2 to n
1680C **** for j = 1 to i-1
1690C **** {cov(i,j) = cov(i,j) + cov(j,i)

```

```

1700C
1710C   for j = 1 to i-1
1720C     covmat{i,j} = mnprod(i,j) - mean(i)*mean(j)
1730C     ccvmat{j,i} = covmat{i,j}
1740C   next j
1750C   goto 2490
1760C   for i = 1 to 4
1770C     verr(i,k) = err(i)
1780C   next i
1790C   if k = 1 then 1850
1800C   if k > window then 2170
1810C   for i = 1 to 4
1820C     wssum(i,k) = verr(i,k) + wssum(i,k-1)
1830C   next i
1840C   goto 1880
1850C   for i = 1 to 4
1860C     wssum(i,k) = verr(i,k)
1870C   next i
1880C   !***** compute the mean of the error *****
1890C   for i = 1 to 4
1900C     wmean(i,k) = (1/k)*wssum(i,k)
1910C   next i
1920C   !***** compute the variance of the error *****
1930C   for i = 1 to 4
1940C     verrsq(i,k) = verr(i,k)*verr(i,k)
1950C   next i
1960C   for k = 1 then 2010
1970C     for i = 1 to 4
1980C       wssumsq(i,k) = verrsq(i,k) + wssumsq(i,k-1)
1990C     next i
2000C     goto 2040
2010C     for i = 1 to 4
2020C       wssumsq(i,k) = verrsq(i,k)
2030C     next i
2040C     for i = 1 to 4
2050C       wmeansq(i,k) = (1/k)*wssumsq(i,k)
2060C       wmean(k) = wmean(i,k)*wmean(i,k)
2070C       wvar(i,k) = wmeansq(i,k) - wmean(k)
2080C     next i
2090C   !***** compute the running product mean *****
2100C   wprod(k) = wprod(k)*verr(i,k)
2110C   if k = 1 then 2140

```

```

2120 wprod(k) = wtprod(k) + wprod(k-1)
2130 goto 2150
2140 wprod(k) = wtprod(k)
2150 wprod(k) = (1/k)*wprod(k)
2160 goto 239C
2170 !***** compute the window statistics *****
2180 fcr i = 1 to 4
2190 wssum(i,k) = werr(i,k) + wssum(i,k-1) - werr(i,k-window)
2200 next i
2210 !***** compute the mean of the error *****
2220 fcr i = 1 to 4
2230 wmean(i,k) = (1/window)*wssum(i,k)
2240 next i
2250 !***** compute the variance of the error *****
2260 fcr i = 1 to 4
2270 werrsq(i,k) = werr(i,k)*werr(i,k)
2280 wsumsq(i,k) = werrsq(i,k) + wsumsq(i,k-1) - werrsq(i,k-window)
2290 next i
2300 fcr i = 1 to 4
2310 wmeansq(i,k) = (1/window)*wsumsq(i,k)
2320 wmeanksq(i,k) = wmean(i,k)*wmean(i,k)
2330 wvar(i,k) = wmeansq(i,k) - wmeanksq(i,k)
2340 next i
2350 !***** compute the running product mean *****
2360 wtprod(k) = werr(s,k)*werr(t,k)
2370 wprod(k) = wtprod(k) + wprod(k-1) - wtprod(k-window)
2380 wprod(k) = (1/window)*wprod(k)
2390 covmat(s,s) = wvar(s,k)
2400 covmat(t,t) = wvar(t,k)
2410 covmat(s,t) = wprod(k) - wmean(s,k)*wmean(t,k)
2420 cccv(k) = covmat(s,s)*covmat(t,t)
2430 if k = 1 then 248C
2440 if cccv(k) > cccv(k-1) then up = up + 1 @ down = 0
2450 if cccv(k) < cccv(k-1) then down = down + 1 @ up = 0
2460 if up = increase then upflag = 1 @ up = 0
2470 if down = decrease then downflag = 1 @ down = 0
2480 if statplt = 1 then read # 4: covmat(s,s), covmat(t,t),
2490 covmat(s,t) @ goto 2500
2500 !***** covmat(s,s), covmat(t,t), covmat(s,t) *****
2510 !***** fcr error ellipse *****
2520 if k = first or (k-first) mod nr = 0 then 2530 else 3370

```

```

2530 count = count + 1
2540 if pplot = 1 then 2590
2550 ekk{1} = covmat{s,s}
2560 ekk{2} = covmat{t,t}
2570 ekk{3} = covmat{e,t}
2580 goto 2600
2590 mat ekk = per
2600 lx = ekk{1}
2610 ly = ekk{2}
2620 mmax = max{lx,ly}
2630 mmin = min{lx,ly}
2640 if mmin < 0 then 3290
2650 if mmax/mmin < 10000 then 2670
2660 if mmax = lx then llarge = 1 else llarge = 2
2670 if ekk{3} < 0 then 2700
2680 if theta = 0
2690 goto 2770
2700 if ekk{1} < ekk{2} then 2730
2710 if theta = 0
2720 goto 2770
2730 theta = .5*atn(2*ekk{3}/ekk{1}-ekk{2})
2740 lx = {ekk{1} + ekk{2}}/2 + ekk{3}/sin{2*theta}
2750 ly = {ekk{1} + ekk{2}}/2 - ekk{3}/sin{2*theta}
2760 if lx < 0 or ly < 0 then 3370
2770 a = sqrt{lx}
2780 b = sqrt{ly}
2790 area = 3.1416*a*b
2800 if plotarea = 1 then 3360
2810 if k = first then 2840
2820 if count = 1 and sscale = 1 then 2840
2830 goto 2880
2840 smax = max{a,b}
2850 if smax < .000001 then 3290
2860 fscale = 2*smax
2870 pscale = -(2*smax)
2880 if pl = 1 then fplotter is 1 else plotter is 805
2890 if cl < c then 2930
2900 pt = chg - .5
2910 pclear
2920 if pl = 0 then limit 28,241,35,184
2930 if pl = 1 then locate 25,145,16,90 else locate 30,108,18,96
2940 scale nscale,pscale,nscale,pscale

```

```

2950 if cl <> 0 then 3020
2960 mcve .8*pscale,.1*nscale
2970 label "x-position (ft)"
2980 mcve .2*pscale,1.05*pscale
2990 label "y-position (ft)"
3000 mcve .9*pscale,1.05*pscale
3010 label "time:" area {sg ft} ":" legend"
3020 if sscale <> 1 and k <> first then 3050
3030 if cl = 0 then laxes pscale/2,pscale/2,0,0
3040 goto 3060
3050 if pl <> 1 and cl = 0 then laxes pscale/2,pscale/2,0,0
3060 mcve .9*pscale,1*chq*pscale
3070 if llarge = 0 then 3120
3080 if llarge = 1 then label using 3090: " "k:" "area:" y-axis"
else label using 3090: " "k:" "area:" y-axis"
3090 image 2a,dd,2a,4de,7a
3100 llarge = 0
3110 goto 3170
3120 if count = 1 then label using 3160: " "k:" "area:"
3130 if count = 2 then label using 3160: " "k:" "area:"
3140 if count = 3 then label using 3160: " "k:" "area:"
3150 if count = 4 then label using 3160: " "k:" "area:"
3160 image 2a,dd,2a,4de,6a
3170 move 0,0 = 2 then line type 3
3180 if count = 3 then line type 5
3190 if count = 4 then line type 1
3200 if count = 0 tc 360 step 5
for ang = ccs(ang)*a
xx = sin(ang)*t
yy = xx*cos(theta) - yy*sin(theta)
yy1 = yy*cos(theta) + xx*sin(theta)
iplot xx,yy1
next ang
goto 3310
disp "no ellipse plotted, out of scale for k="k
goto 3370
cl = cl + 1
pt = pt - .4
if cl = chg then cl = 0
if count = chg then count = 0
goto 3370

```

```

336C      disp "k=":k:area
3370      next k
3380      assign# 1 to *
3390      assign# 2 to *
3400      assign# 3 to *
3410      assign# 4 to *
3420      assign# 5 to *
3430      assign# 6 to *
3440      assign# 7 to *
3450      end

```


LIST OF REFERENCES

1. Sorenson, H.W., "Kalman Filtering Techniques", Advances in Control Systems, v. 3, pp. 219-292, Academic Press, 1966.
2. Kirk, D.E., EE4413 Class Notes "Optimal Estimation: An Introduction to the Theory and Applications", (unpublished), Naval Postgraduate School, 1975.
3. Jazwinski, A.H., Stochastic Processes and Filtering Theory, Academic Press, 1970.
4. Cramer, H., Mathematical Methods of Statistics, Princeton University Press, 1961.
5. Mitschang, G.W., An Application of Nonlinear Filtering Theory to Passive Target Location and Tracking, PhD Dissertation, Naval Postgraduate School, 1974.
6. Heffes, H., "The Effects of Erroneous Models on the Kalman Filter Response", IEEE Trans. Automatic Control, v. 11, pp. 541-543, 1966.
7. Nishimura, T., "Error Bounds of Continuous Kalman Filters and the Application of Orbit Determination Problems", IEEE Trans. Automatic Control, v. 12, pp. 268-275, 1967.

BIBLIOGRAPHY

Anderson, B.D., and Moore, J.B., Optimal Filtering, Prentice Hall, 1979.

Meditch, J.S., Stochastic Optimal Linear Estimation and Control, McGraw-Hill, 1969.

Sage, A.P., and Melsa, J.L., Estimation Theory with Applications to Communications and Control, McGraw-Hill, 1971.

Ladas, J.E., Interactive Monte Carlo Simulation Program for Evaluation of Estimators and Predictors for Fire Control Systems, Master's Thesis, Naval Postgraduate School, 1981.

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